Artificial Intelligence for Engineering Design, Analysis and Manufacturing

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Sitting posture detection and recognition of aircraft passengers using machine learning

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Research Article

Cite this article: Cun W *et al* (2021). Sitting posture detection and recognition of aircraft passengers using machine learning. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing* **35**, 284–294. https://doi.org/10.1017/S0890060421000135

Received: 10 November 2020
Revised: 13 May 2021
Accepted: 16 May 2021
First published online: 2 September 2021

Key words:
Aircraft passenger; comfort; detection; machine learning; recognition; seat design; sitting posture

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Abstract

Prolonged sitting in a fixed or constrained position exposes aircraft passengers to long-term static loading of their bodies, which has deleterious effects on passengers' comfort throughout the duration of the flight. The previous studies focused primarily on office and driving sitting postures and few studies, however, focused on the sitting postures of passengers in aircraft. Consequently, the aim of the present study is to detect and recognize the sitting postures of aircraft passengers in relation to sitting discomfort. A total of 24 subjects were recruited for the experiment, which lasted for 2 h. Furthermore, a total of 489 sitting postures were extracted and the pressure data between subjects and seat was collected from the experiment. After the detection of sitting postures, eight types of sitting postures were classified based on key parts (trunk, back, and legs) of the human bodies. Thereafter, the eight types of sitting postures were recognized with the aid of pressure data of seat pan and backrest employing several machine learning methods. The best classification rate of 89.26% was obtained from the support vector machine (SVM) with radial basis function (RBF) kernel. The detection and recognition of the eight types of sitting postures of aircraft passengers in this study provided an insight into aircraft passengers' discomfort and seat design.

Introduction

In recent years, the competition among airlines has become increasingly fierce in relation to an increasing demand for air travel. In this regard, improving passengers comfort has become the primary strategy for airlines to increase competitiveness (Hiemstra-van *et al.*, 2016; Li *et al.*, 2017). During the flight, the most imperative part of an aircraft cabin is the seat, owing to the fact that aircraft passengers spend most time of their trips sitting on their seats (Ciaccia and Sznelwar, 2012). Sitting in a restricted or fixed position for a long time could result in long-term body static load, which is regarded as a risk factor for discomfort, musculoskeletal complaint and disorder (Fazlollahtabar, 2010; Luttmann *et al.*, 2010; Cascioli *et al.*, 2011). Besides, in terms of the human perception, aircraft passengers are affected by the psychological invasion of personal space in the narrow and enclosed environment (e.g., the small seat space and active areas), which is often a contributory factor to the ordeal of discomfort (Lewis *et al.*, 2017). This discomfort induced by invasion will also reflect on passengers' sitting postures; thus, passengers tend to lean to the side of the empty seat. Consequently, research on passengers' sitting postures has been an important strategy to reduce passengers' discomfort and can be employed to measure emotions, discomfort, physical wellness, and healthy sitting behavior (Tan *et al.*, 2001; Tessendorf *et al.*, 2009; Lan *et al.*, 2010; Foubert *et al.*, 2012).

In terms of sitting postures studies, Mastrigt *et al.* (2016) discussed the relationship among context, seat, behavior, sitting posture, cushion pressure, and discomfort in aircraft (Fig. 1). According to Mastrigt *et al.* (2016), the sitting postures of aircraft passengers were influenced by three factors: (1) human anthropometry, such as height, body mass, and hip circumference; (2) seat, such as dimensions, shape, and reclined backrest angle; and (3) context, which include activities and the environment. A similar research by Vanacore *et al.* (2019) on posture induced by activity (Kamp *et al.*, 2011; Ellegast *et al.*, 2012; Groenesteijn *et al.*, 2012), and effect of posture on seat-interface pressure distribution (Vos *et al.*, 2006; Moes, 2007; Tessendorf *et al.*, 2009; Kyung and Nussbaum, 2013), showed the closest correlation between objective measure and subjective (dis-)comfort rating. Thus, human anthropometry, seat, and context should be involved in the study of sitting postures.

Recent advancement in machine learning has culminated in the application of machine learning algorithms in many studies, such as prediction of the three-dimensional posture of the spine in various activities (Gholipour and Arjmand, 2016), prediction of the subjective perceptions of drivers' comfort (Kolich, 2004) and classification of sitting postures (Zhu *et al.*, 2003; Meyer *et al.*, 2010; Zemp *et al.*, 2016; Ma *et al.*, 2017). Machine learning has also been applied in research bordering on aircraft passengers' discomfort as well as seat design

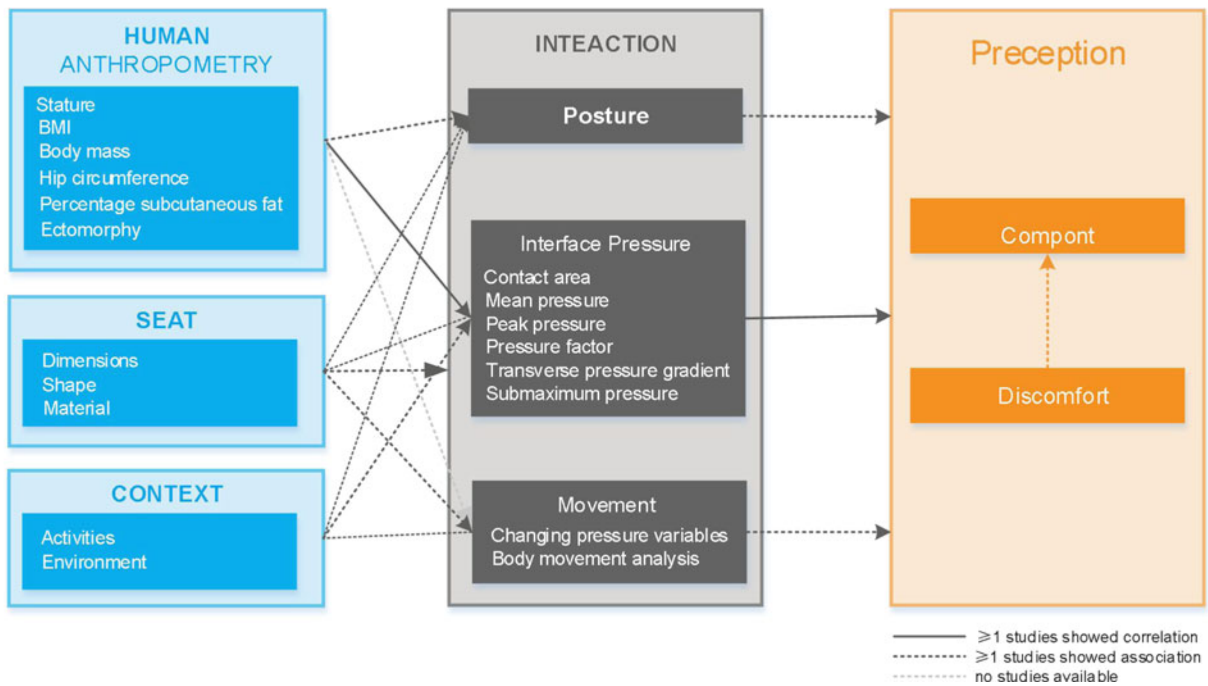

Fig. 1. Overview of relationships between the variables.

and manufacturing. Aircraft seat sensors can provide some feedback information, which can help to identify passengers' status and comfort in the near future with machine learning. Airbus commercial laboratory pointed out that the measurement of the lifting frequency of intelligent seat armrest employing sensors can provide guidance for design engineers on how to carry out armrest durability design. Thus, the detection and recognition of sitting postures employing machine learning methods have been widely studied because of its potential in improving people's comfort and forestalling the occurrence of related diseases. It can adequately educate chair users about their sitting postures (Zubic, 2007) and guide them in adopting beneficial postures that could efficaciously prevent workplace musculoskeletal diseases (Yoo *et al.*, 2006). According to Mutlu *et al.* (2007), posture recognition could help infer emotional states, detect irregular behaviors, and control human–computer interaction applications. The research above provided a theoretical basis and foundation for the adoption of machine learning methods to study aircraft passengers' sitting postures. Consequently, machine learning methods will be exploited in this study to detect and recognize the sitting postures of aircraft passengers.

There are two main types of sitting posture measurement: image processing technology (Lan *et al.*, 2010; Song-Lin and Rong-Yi, 2010) and sensor-based technology (Li *et al.*, 1999; Tan *et al.*, 2001; Kamiya *et al.*, 2008; Tessendorf *et al.*, 2009; Foubert *et al.*, 2012). Image recognition is easy, noninvasive, and user-friendly, but be complicated by variations in the lighting or background condition, camera or subject positions, and subject appearance (Mota and Picard, 2008). In addition, passengers' privacy will be violated if cameras are installed in aircraft. Compared with image processing technology, pressure sensors can accurately collect the pressure information between passengers and seat in real-time, which will aid research on the discomfort of aircraft passengers. Furthermore, passengers' sitting postures can be detected in real-time employing pressure sensors which could help detect (1) the duration of their static sitting postures, (2) the frequency of changes in their sitting postures and muscle force, and (3) load on specific body parts, etc. Thus, pressure sensors were exploited to detect and recognize sitting postures in many researches.

The recognition of sitting posture employing pressure sensors that has long been studied by researchers. The concept of instrumented or sensing chairs was first introduced by Tan and co-workers (Tan *et al.*, 2001; Tan and Ebert, 2002). The authors placed surface-mounted pressure distribution sensor mats over the seat pan and the backrest to obtain real-time information of the chair–user interaction. Mota and Picard (2008) employed the same measuring system to analyze nine different sitting positions but in a dynamic setup. In order to teach the pattern recognition algorithm, two observers labeled the different sitting positions employing video analysis, which produced an overall classification accuracy of 87.6% in new subjects. Tessendorf *et al.* (2009) employed pressure distribution patterns acquired from a pressure mat to generate 16 prototype sitting postures which they used to classify incoming pressure data. Similarly, Xu *et al.* (2012) developed a technique to recognize nine different sitting postures based on binary pressure distribution data. Meanwhile, in order to reduce the complexity and cost of the measurement system, some studies focused on the analysis of sitting postures using several single axis force or pressure sensors apart from the pressure distribution sensor mat. Schrempf *et al.* (2011) proposed a method based on a regular adjustable office chair which was equipped with four independent, specially designed force transducers; Meyer *et al.* (2010) employed a textile pressure sensor mat with 96 elements on the seat pan and 1 element on the backrest to classify 16 different static sitting positions. The Smart Cushion system introduced by Xu *et al.* (2013) consists of a 16 × 16 textile pressure sensor mat placed at the seat pan of a conventional chair. By applying a time warping-based classification algorithm, an accuracy level of almost 86% was achieved for seven different postures. Zemp *et al.* (2016) developed an instrumented chair with force and acceleration sensors to determine the accuracy of automatic identification of the user's sitting position by applying five different machine

Table 1. Demographic characteristics of the participants (n = 24)

Age (years)	Male: Female	Height (m)	Body mass (kg)	BMI (kg/m^2)
25.29 ± 2.64	1:2	1.69 ± 0.07	61.21 ± 11.64	21.45 ± 3.27

learning methods. The classification accuracy varied between 81% and 98% for the seven different sitting positions. Jongryun *et al.* (2018) developed a system that measured a total of six sitting postures and demonstrated the possibility of classifying the sitting postures even though the number of sensors was reduced. The above-reported studies demonstrate that it is possible to detect different sitting postures with considerable accuracy by means of conventional and single axis force sensor mats. In this study, pressure sensors [Body Pressure Measurement System (BPMS) of Tekscan] were employed to ensure a flawless and precise recognition accuracy.

Among the studies conducted on sitting postures, we found that passengers' sitting postures play an important role in the discomfort of aircraft passengers. However, there are few studies that have analyzed the sitting postures of aircraft passengers to the best of our knowledge. Most of the studies focused on the discomfort induced by office chairs and driver's seats (Mastrigt *et al.*, 2016). Furthermore, the sitting postures adopted in previous studies did not involve factors of human anthropometry, seat, and context and was inconsistent with the actual sitting postures. In addition, pressure sensors could detect different sitting postures with considerable accuracy, making them a suitable method for detecting passengers' sitting postures. Thus, the aim of this study is to detect the sitting postures of aircraft passengers and recognize these postures employing several machine learning methods. Based on the above studies, two hypotheses were constructed in this paper: (1) Several types of specific sitting postures of aircraft passengers would be obtained from the flight simulated experiment. (2) The sitting postures classified above would be recognized with pressure sensor data using machine learning methods with ideal accuracy.

In this study, the term sitting posture is used to connote posture that is related to movement of the trunk, back, and legs of passengers' body when they were strapped to the seat. Activities refer to the specific behavior of passengers such as eating, working, and sleeping, while behavior refer to an action in a general sense.

Materials and methods

Subjects

A total of 24 Chinese subjects (16 females and 8 males) in the age bracket of 22–30 were recruited. The demographic characteristics are presented in Table 1. It shows the subjects' indicators [age, height, body mass, and body mass index (BMI)] and their related descriptive statistics, expressed as mean ± standard deviation. The sample of 16 females and 8 males (height ranging from 1.56 to 1.80 m) may represent the mean and larger percentiles of Chinese people (Li *et al.*, 2017). Participants were carefully selected; the subjects were pain free and healthy. Informed consent was obtained from participants and the study was approved by the Ethics Committee of Northwest Polytechnic University.

Experimental design

We conducted our experiment in a laboratory situated in Northwest Polytechnic University. The room temperature of the laboratory was 23 ± 2°C, the relative humidity was between 48% and 60% (Li *et al.*, 2017), and the environment noise level was set to 40–60 dB.

Before the experiment, participants had about 10 min to relax and prepare and were fully informed of the content, duration of the experiment, the purpose of the study, and the methods for analysis of the collected data. In order to make subjects exhibit real feelings and behaviors during the experiment, we had a conversation with them about their previous feelings before the experiment, in a bid to evoke their flying experiences.

During the experiment, subjects took turns to complete the following activities according to the instruction of the experimenter: used mobile phone for 10 min, chatted for 20 min, worked for 25 min, ate for 15 min, and slept for 50 min. Subjects were not given any additional guidance or feedback except five predefined sequential activities as our goal was to obtain subjects' natural sitting postures. During the 2 h experiment, subjects' sitting postures data was recorded with two pressure sensors [Body Pressure Measurement System of Tekscan (BPMS), South Boston, MA, USA] and a video camera in real-time. Pressure data was recorded at 5 Hz with the BPMS software matched with the pressure mat in order to obtain more precise data from the two pressure sensors. The movements and postures of participants were recorded by a video camera during the whole experiment. The experiment involving human subjects carried out in the laboratory is shown in Figure 2. The experiment would be terminated once an anomaly is observed in the data of the two pressure sensors and camera during the experiment. It should be noted that the 2 h duration setting of this experiment was aimed at studying the sitting posture of regional airliner in short and medium-haul flight.

After the experiment, participants' demographics (gender, age, height, body mass, and BMI) were measured and the participants were thanked for their participation. The flowchart of the experiment is shown in Figure 3.

Sitting postures detection

The sitting postures reported in previous studies are summarized in Table 2. As can be seen from the table, the sitting postures reported in different studies were completely different. Moreover, these sitting postures adopted by many studies emanated from either the earlier studies or defined by the authors with less contextual information. For example, the sitting postures reported in Zemp *et al.* (2016) emanated from previous studies (Mota and Picard, 2003; Haller *et al.*, 2011; Xu *et al.*, 2013). Furthermore, the sitting postures reported by Haller *et al.* (2011) were predefined directly by them. However, as mentioned above, sitting postures were influenced by human anthropometry, seat, and context. Thus, this study went a step further in the classification of passengers' sitting postures.

In our experiment, flight scenario was simulated with subjects of a variety of human anthropometry. The five most common activities were set, which basically covered the three factors (human anthropometry, seat, and context) that influenced the sitting postures of passengers. After the analysis of sitting posture data, we found that the sitting postures of each subject varied a little due to individual differences and personal habit, and each subject exhibited only a limited number of specific sitting postures. Although the sitting posture of each subject was not the same, they still had something in common.

In the experiment, it was found that activities had a great influence on the sitting postures and the postures of different activities

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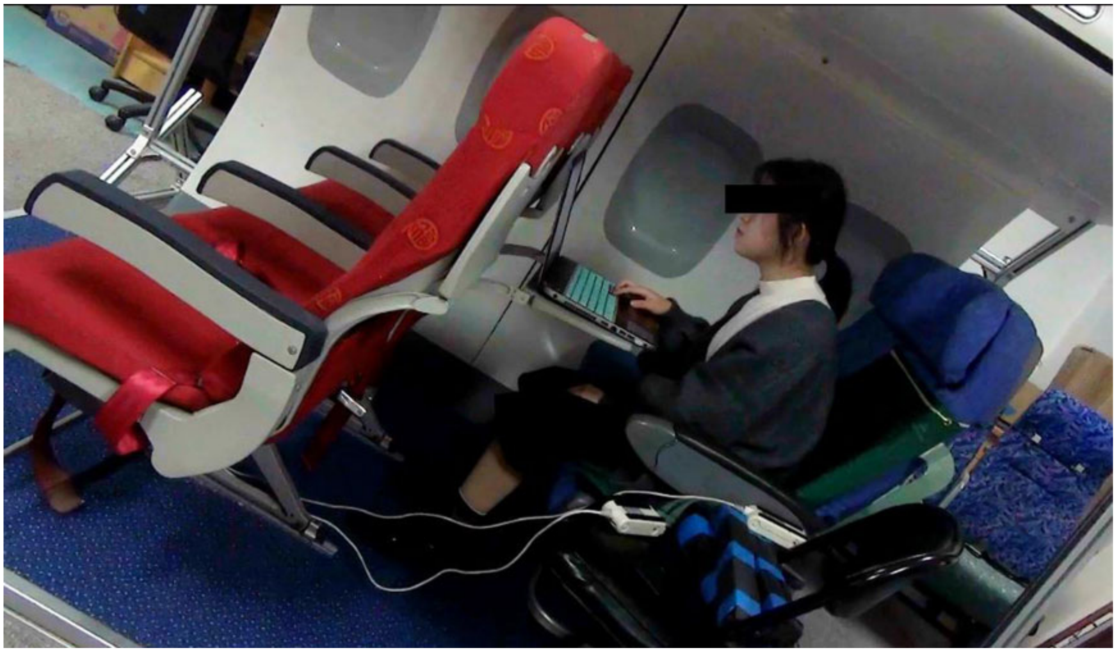

Fig. 2. Experiment of subjects in the laboratory (the length, width, height, and seat pitch of the seat are 53, 52, 116, and 98 cm, respectively).

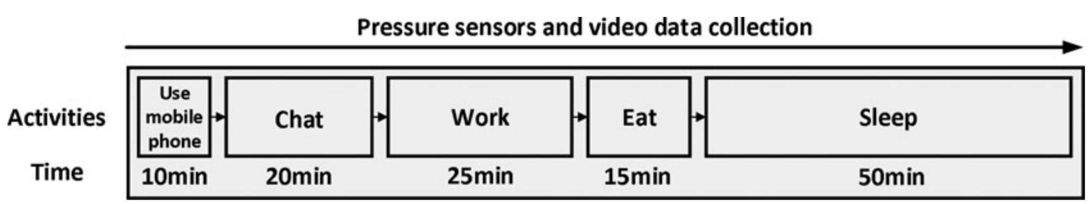

Fig. 3. Flowchart of the experiment.

were different. Specifically, subjects exhibited a proclivity for leaning forward when they worked. Contrarily, they leaned backward when they assumed a relaxed and resting posture (i.e., chat, use mobile phone, eat, and sleep). Besides, subjects changed several postures owing to the long duration of sleep. Also, subjects maintained one posture for a long time because of the inactive state of the body. All the changes associated with the five activities mentioned above reflected on the positions of three key parts of the subjects' body (i.e., trunk, back, and legs). Thus, the three key parts of the subjects' body were the most imperative body parts that affected passengers' sitting postures. For example, when subjects leaned forward, their trunks moved forward; when they leaned backward, the position of their trunks was opposite. The same situation was observed when subjects leaned to the right and left. In addition, when subjects crossed their legs, there was a significant change in the sitting postures. Based on the above analysis, the sitting postures were classified according to the positions of the three key parts of the body, which we described further in the "The recognition of sitting posture" section.

Sitting postures recognition methods

In the data analysis, we discovered that each posture of the 24 subjects was maintained for a period of time and then changed into another posture. In other words, although the experimental time lasted for 2 h, each subject exhibited only about 20 postures. Thus, 489 sitting postures were extracted from the experimental video and the pressure data of the 489 sitting postures was employed to construct machine learning models. Each pressure data of the 489 sitting postures contained 16 dimensions pressure data, while the whole model involved 7824 pressure data. The 16 dimensions pressure data refers to the 8 dimensions pressure data (i.e., object pressure, peak object pressure, peak contact pressure, peak force, contact area, contact pressure, force, and force center) of the backrest and seat pan, respectively.

Previous studies showed that several different machine learning methods were exploited for the classification of sitting postures (Zemp *et al.*, 2016; Jongryun *et al.*, 2018). In this study, five algorithms [K-nearest neighbor, support vector machine (SVM), random forest, decision tree, and Naïve Bayes] were compared to obtain the highest classification accuracy.

(1) K-nearest neighbor

K-nearest neighbor algorithm categorizes different classes by measuring the distance between different eigenvalues (Cover and Hart, 2003). Its working principle is hinged on the existence of a sample data set, also known as the training sample set, and each data in the sample set has a label that shows the corresponding relationship between each data in the sample set and its classification. After inputting the new data without labels, each feature of the new data was compared with several corresponding

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Table 2. Summary of previous studies on sitting postures definition and recognition

Authors and year	Posture resources	Posture context	Postures
Tan *et al.*, 2001	Author predefined with previous studies	In the office	1. Seated upright; 2. Leaning forward; 3. Leaning left; 4. Leaning right; 5. Right leg crossed (with knees touching); 6. Right leg crossed (with right foot on left knee); 7. Left leg crossed (with knees touching); 8. Left leg crossed (with left foot on right knee); 9. Left foot on seat pan under right thigh; 10. Right foot on seat pan under left thigh; 11. Leaning left with right leg crossed; 12. Leaning right with left leg crossed; 13. Leaning backward; and 14. Slouching
Haller *et al.*, 2011	Author predefined with no previous studies	In the office	1. Upright; 2. Leaning back; 3. Leaning forward; 4. Sitting at the front edge; 5. Leaning right; 6. Right leg crossed over left leg; 7. Left leg crossed over right leg; and 8. Slouching
Huang and Ouyang, 2013	Author predefined with no previous studies	None	1. Sitting on chair surface and backrest; 2. Sitting on chair surface, but not touching backrest; 3. Crossing legs; 4. Crossing legs; and 5. Crooked sitting posture
Zemp *et al.*, 2016	Author predefined postures with previous studies	In the office	1. Upright position; 2. Reclined position; 3. Forward inclined position; 4/5. Laterally tilted right/left position; and 6/7. Crossed legs, the left leg over the right one/the right leg over the left one
Jongryun *et al.*, 2018	Author predefined with previous studies	In the office	1. Upright sitting with backrest; 2. Upright sitting without backrest; 3. Front sitting with backrest; 4. Front sitting without backrest; 5. Left sitting; and 6. Right sitting

features of the sample data, and then the classification labels of the most similar data (nearest neighbor) of the sample were extracted. In this study, the best classification performance was achieved when n_neighbors were set to 6 after grid searching for different parameters.

(2) Support vector machine

Support vector machine is a group of supervised learning methods that can be used for classification or regression purposes (Burges, 1998; Gao *et al.*, 2010). It is a two class classification model. Its basic model is defined as the linear classifier with the largest interval in the feature space. Its learning strategy is to maximize the interval, which can be transformed into a convex quadratic programming problem. In this study, the best classification performance was achieved when radial basis function (RBF) kernel was employed and the regularization coefficient was set to 5 after the trial of different parameters.

(3) Random forest

In machine learning, random forest is a classifier with multiple decision trees, and the output category is determined by the mode of the output category of individual trees (Breiman, 2001). Random forest integrates multiple trees by exploiting the idea of ensemble learning into an algorithm. Its basic unit is decision tree, and its core essence is tied to a big branch of machine learning ensemble learning method. The best classification performance was achieved when n_estimators were set to 800, max_depth was set to 5 after the trial of different parameters in this study.

(4) Decision tree

Decision tree classification algorithm is an inductive learning method that is based on instances in which tree classification models can be extracted from given disordered training samples (Safavian and Landgrebe, 2002). The decision tree algorithm first divides a pile of data into subsets according to a certain condition (feature) to construct a tree. Thereafter, a new data emerges for comparison of the new data one after the other according to the conditions specified during construction of the tree, until the leaf node is found to determine the category. The best classification performance was achieved when the criterion was set to entropy, and random_state was set to 5 after the trial of different parameters.

(5) Naïve Bayes

Naïve Bayes is a classification method based on the Bayes theorem and independent assumption of feature conditions (Bermejo *et al.*, 2014). For a given training data set, the joint probability distribution of input/output is learned based on the independent presumption of characteristic conditions. According to this model, the output with the maximum *a posteriori* probability for a given input is obtained employing the Bayesian theorem. In this study, the model of the algorithm was set to GaussianNB.

In the construction of the machine learning model, the data set of training and test were classified randomly based on the 24 subjects' pressure data (totaling 8313 data), of which 6256 data belonged to the training set and 2057 data belonged to the test set.

In the algorithm analysis, principal component analysis (PCA) was exploited to reduce the dimensionality of the data as well as extract the features (principal components) that represented the most informative data due to the redundancy of the 16 dimensions pressure (Tan *et al.*, 2001). Finally, 16-dimensional pressure data were reduced to 4-dimensional pressure data with 95% of the original data retained. In this regard, on the basis of ensuring the seamless performance of the algorithm, the calculated amount of the model was reduced. In this study, scikit-learn algorithm toolkit based on Python was used to build the machine learning models.

Results

The detection of sitting postures

As mentioned in the "Sitting postures detection" section, the three key parts of the human body (i.e., trunk, back, and legs) were the basis for our classification of the sitting postures of aircraft passengers. Based on the above analysis, and report of previous studies (Zemp *et al.*, 2016; Jongryun *et al.*, 2018), we finally classified

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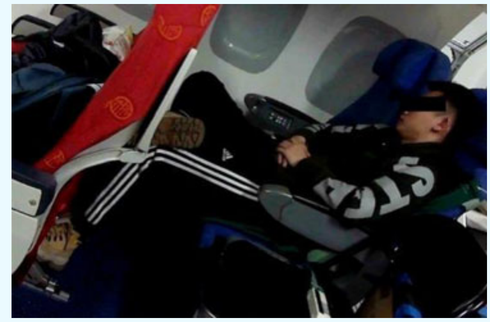
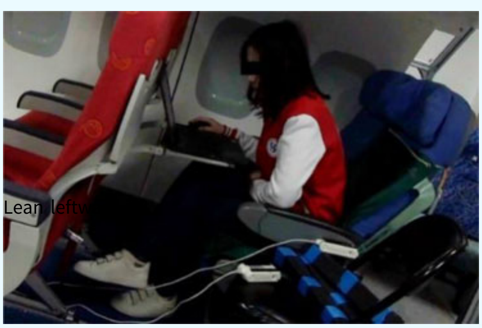
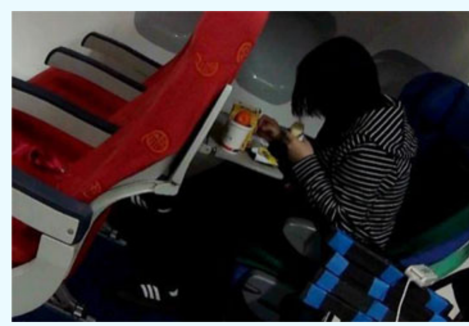
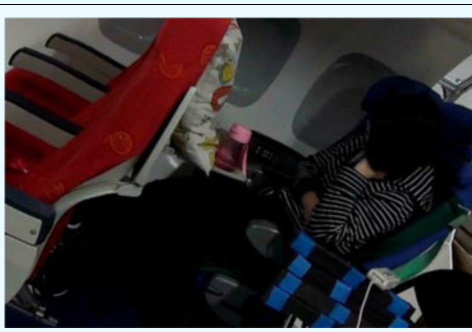
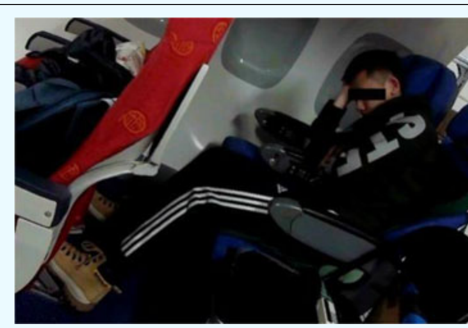
Table 3. The eight types of sitting postures of aircraft passengers

Lean backward	Lean backward, crossed legs right over left
	
Lean backward, crossed legs left over right	Lean forward
	
Lean forward, crossed legs right over left	Lean forward, crossed legs left over right
	
Lean leftward	Lean rightward
	

passengers' sitting postures into eight types, as seen in Table 3. These eight sitting postures were the most prevalent and representative sitting postures of airplane passengers.

As discussed above, the sitting postures in aircraft were different from that of office and driving sitting postures (see Table 2). The uniqueness of aircraft passengers' sitting postures is hinged on: (1) the fact that sitting space is very narrow; (2) passengers will spend several hours in the journey, and most of the time they are strapped to their seats; and (3) passengers perform only a few specific activities, while most people will sleep during the journey. The uniqueness of the above sitting postures induced special sitting postures during the flight. Thus, the eight sitting postures which emanated from the simulation flight experiment could fully reflect the uniqueness (affected by human anthropometry, seat, and context) of aircraft passengers' sitting postures. In this regard, the hypothesis (1) was confirmed.

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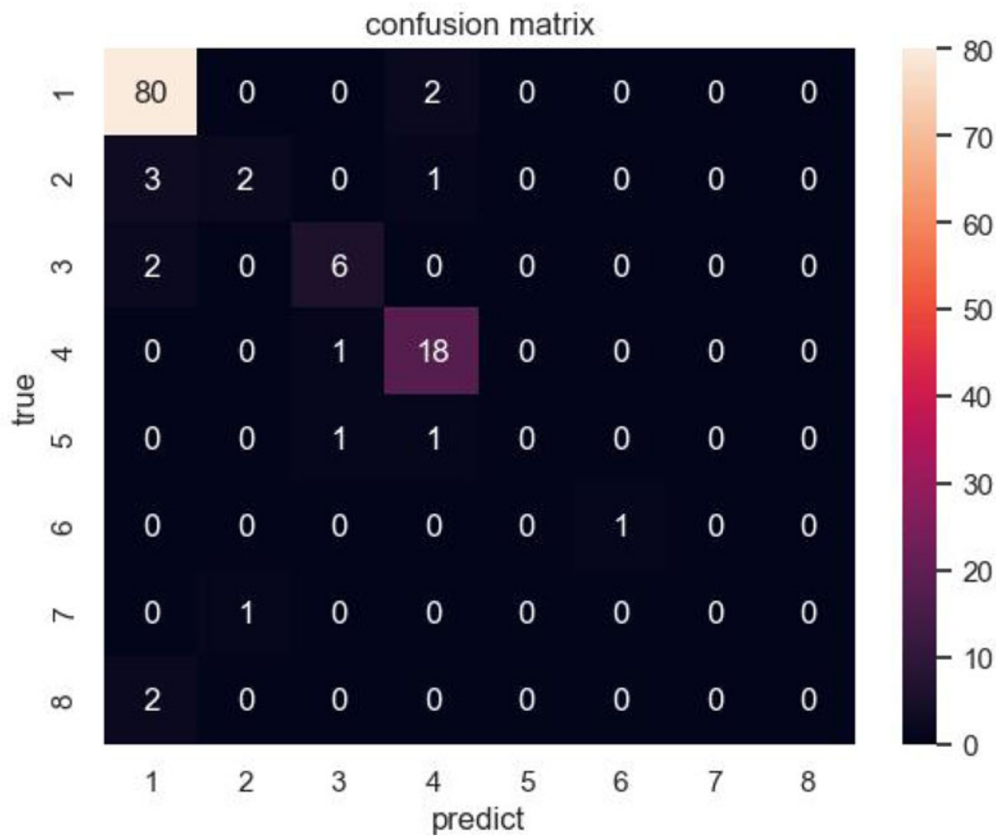

Fig. 4. Confusion matrix of SVM with RBF kernel. Rows indicate predicted labels, columns refer to true classes. Class labels represent 1: lean backward; 2: lean backward, crossed legs right over left; 3: lean backward, crossed legs left over right; 4: lean forward; 5: lean forward, crossed legs right over left; 6: lean forward, crossed legs left over right; 7: lean leftward; and 8: lean rightward.

Table 4. Comparison of sitting postures recognition of different machine learning models based on the pressure data

	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
KNN	82.65	77.33	82.65	79.77
SVM_{RBF}	**89.26**	**85.16**	**89.26**	**86.80**
SVM_{linear}	83.47	79.07	83.41	81.02
Random forest	85.95	82.61	85.95	83.03
Decision tree	77.69	80.74	77.69	78.12
Naïve Bayes	79.34	77.53	79.34	77.94

These bold values are the best performance data among all the models.

The recognition of sitting posture

In this section, the sitting postures classified above were recognized by five machine learning models mentioned in the "Sitting postures recognition methods" section. Regarding the recognition of the sitting postures, the output was eight sitting postures mentioned in the "The detection of sitting postures" section, and the input was the pressure data of the two pressure sensors installed on the backrest and seat pan of the 24 subjects for 2 h. The recognition results were analyzed from four dimensions: accuracy, precision, recall, and F1-score. After loading the pressure data into different machine learning models and debugging different parameters for the best results, we were able to compare several machine learning models. The SVM with RBF kernel attained the best classification accuracy of 89.26%, as shown in Table 4. The results revealed that the random forest model also achieved satisfactory classification results. Thus, the hypothesis (2) was also confirmed.

The confusion matrix of SVM with RBF kernel is presented in Figure 4. From the confusion matrix of SVM, sitting postures 1 (leaning backward) and 4 (leaning forward) were the two most accurate postures predicted by the model.

Discussion

This study focused on sitting posture detection and recognition of aircraft passengers. A total of eight types of sitting postures of subjects were classified through the flight simulation experiment and recognized according to the seat pressure sensors data employing machine learning models. Among several machine learning methods, SVM with RBF kernel attained the best classification performance of 89.26%, which showed that seat pressure sensors data had good classification capacity for the recognition of aircraft passengers' sitting postures. Based on the classification results, we can distinguish passengers' sitting postures employing the pressure data of seat in order to improve the comfort and experience of aircraft passengers.

As discussed above, sitting postures were affected by human anthropometry, seat, and context. However, the sitting postures of previous studies did not involve these three factors, as seen in

Table 5. Comparison of sitting posture classification of previous studies and this study

Author and year	Number of sensors	Location of sensors	Number of subjects	Classification algorithm	Number of postures	Classification accuracy (%)
Zhu *et al.*, 2003	Pressure sensor sheets (42 × 48 pressure sensor)	Seat plate and backrest	50	Slide inverse regression	10	86
Zemp *et al.*, 2016	16 pressure sensors	Seat plate, backrest, and armrest	41	Random forest	7	90.9
Meyer *et al.*, 2010	96 pressure sensors	Seat plate	9	Naïve Bayes	16	82
Jongryun *et al.*, 2018	4 load cells	Seat plate	9	SVM using RBF kernel	6	97.20
Proposed method	Pressure sensor sheets (32 × 32 pressure sensor)	Seat plate and backrest	24	SVM using RBF kernel	8	89.26

Table 2. In our experiment, the sitting postures obtained fully reflected the three factors and therefore were more in line with the real scene. Furthermore, we found that the three factors that affected sitting postures would ultimately be reflected in trunk, back, and legs of the human body. Based on the above analysis, all the sitting postures in our experiment (totaling 489 sitting postures) were classified into eight types, which were the most prevalent and representative sitting postures of airplane passengers. Thus, the sitting postures classification method demonstrated in this study provides a insight for the study of sitting postures that sitting postures are not isolated, but closely related to human activities and context.

There were two methods employed for the recognition of sitting postures. One was to induce the corresponding sitting posture. Another method was to collect the pressure data of subjects' sitting postures in real context, which we adopted in this study. In the first method, their effect has focused on recognition of static postures made by participants who intentionally position themselves into postures as requested and predefined by the experimenter. Then, the experimenter collected the cushion pressure data which was used to recognize the sitting postures. This kind of research could generally produce a high recognition accuracy, but the disadvantage is that these postures are deliberately made by the subjects, with no real context information. However, as mentioned above, passengers' sitting postures were greatly influenced by the context and other factors. These isolated postures did not match passengers' real sitting postures. Table 5 shows the comparison of sitting posture classification between previous studies and the proposed method. Although the classification accuracy of this study was not the highest, the recognition of sitting postures in this study was still valuable. Firstly, we gathered data of naturally occurring postures, as opposed to the other studies presented in Table 5, in which their postures were deliberately made and with few context factors. Secondly, the sitting postures of other studies presented in Table 5 were all in office context, with no aircraft passengers' sitting posture. Hence, the eight types of sitting postures we classified in this study provided foundation for aircraft passengers' sitting postures. It should be noted that the purpose of this study was not to achieve the highest classification accuracy, but to demonstrate and prove the feasibility of our research method. In other words, the acceptable high recognition accuracy could still be obtained through the natural sitting postures. Therefore, this study provides a new idea that sitting postures should be detected within their specific scene, rather limited to the deliberately setting. This type of recognition of sitting postures holds high practical application value for passengers' comfort (Zhu *et al.*, 2003; Zemp *et al.*, 2016).

The detection and recognition with machine learning methods of passengers' sitting postures promises potential advancement in terms of passengers' discomfort as well as seat design and manufacturing. Passengers' discomfort could be measured by the pressure data of the sitting postures. According to Arnrich *et al.* (2010b), sitting posture could be used for measuring healthy sitting behaviors. Passengers' sitting postures could be detected in real-time with seat pressure sensors, which could help detect the duration of their static sitting postures, change frequency of their sitting postures, muscle force and load on specific body parts, etc. During the flight, passengers may change their postures owing to cumulative fatigue when they maintain a stationary posture for a period of time. This type of change in posture could be detected by pressure data. A similar research by Le *et al.* (2014) showed that frequent movements by the driver over time helped reduce stress from discomfort. In this regard, passengers' discomfort could further be reduced by seat design. The studies of De Looze *et al.* (2003), Franz *et al.* (2011), and Zemp *et al.* (2015) indicated that a large contact area between the seat and human body decreased the effect of discomfort perception. Therefore, Smulders *et al.* (2016) presumed that developing an aircraft seat based on human contour could ameliorate pressure distribution and accordingly decrease discomfort perception. Also, the seat could be designed to adjust automatically or be realigned to prevent muscle fatigue and even diseases induced by long-term fatigue and static sitting in relation to the detection and recognition of sitting postures. Furthermore, passengers' potential needs could be satisfied by seat design that permits automatic adjustment of seat's angle to promote healthier sitting behaviors for passengers, and facilitate the turning off of lights when passengers fall asleep, etc. Posture channel also contains affective information related to passengers' experience. With posture recognition, posture sequences could be conducted to discover affective interpretations associated with postural behaviors. Bull presented results showing that both body movements and positions transmit information about emotions. For example, the upsetting passengers may reveal higher variance of movements. In a further study, Arnrich et al. (2010a) incorporated sensor technology into an airplane seat with the aim of unobtrusively measuring physiological signals to recognize passengers' emotion with reliable and unobtrusive recording of relevant physiological signals. Therefore, the integration of multiple physiological measures (near-infrared spectroscopy, electromyography, electrocardiography, skin electricity, etc.) into the sensing chair to measure the discomfort and experience of passengers is also a direction of seat design.

On the basis of previous studies, several existing classical machine learning methods were compared in this study. After comparing KNN, SVM with linear kernel and RBF kernel, Random Forest, Decision Tree, and Naïve Bayes with the trial of different parameters on the four indexes (i.e., accuracy, precision, recall, and F1-score), SVM with RBF kernel was found to have the highest recognition accuracy. Compared with other studies presented in Table 5, it was found that the algorithm attained the highest recognition accuracy was different in terms of different types of sitting postures. Consequently, different machine learning methods should be explored to achieve the highest recognition accuracy of sitting postures in follow-up studies. In this study, the posture that achieved the highest classification accuracy was sitting posture 1 (leaning backward). Interestingly, according to Zemp *et al.* (2016), sitting posture 4 (leaning forward) had the highest classification accuracy. The reason for this difference can be attributed to the different sitting contexts. In Zemp *et al.* (2016) study, people tended to lean forward when they were working in office, while in this study, passengers tended to lean backward for relaxation in flight. This difference also confirmed that sitting postures were affected by the context.

There were some limitations associated with this study. Limited to the experimental environment, we could only simulate passengers sitting activities in the simulated laboratory. In addition, the ages of our experimental subjects varied from 22 to 30; so, the results are only suitable for Chinese in the same age bracket. Mastrigt *et al.* (2016) reported that sitting postures and pressure distribution are also influenced by age. Seat surface temperature is also a factor that affects the sitting postures of passengers. Sitting on the seat for a long time will cause the skin surface temperature of the human body parts in contact with the seat to rise, causing discomfort (Hales and Bernard, 1996; Lengsfeld *et al.*, 2000; Konz, 2002; Szeto *et al.*, 2002). In this scenario, passengers would change their sitting postures to relieve discomfort. In this study, although we used the seat in the plane to conduct the experiment, subjects' buttock and back were not directly in contact with the seat surface and backrest, but with the pressure cushion. Consequently, the sitting postures of subjects were also affected by the pressure sensors.

Conclusion

This study has explored the detection and recognition of aircraft passengers' sitting postures. In the flight simulated experiment, eight types of sitting postures were detected based on the trunk, back, and legs of the human body and recognized with pressure sensors by SVM with RBF kernel that achieved the classification rates of 89.26%. The recognition of aircraft passengers' sitting postures provided some reference point and baseline information on aircraft passenger discomfort. Furthermore, intelligent seat can be designed by the recognition of passengers' sitting posture, which could be employed to detect passengers' sitting postures at any time and respond automatically to passenger's potential needs in aircraft.

Competing interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

References

Arnrich B, Kappeler-Setz C, Schumm J and Trooster G (2010a) *Design, Implementation and Evaluation of a Multimodal Sensor System Integrated Into an Airplane Seat*. Sensor Fusion – Foundation and Applications.

Arnrich B, Setz C, Marca RL, Troster G and Ehlert U (2010b) What does your chair know about your stress level? *IEEE Transactions on Information Technology in Biomedicine* **14**, 207–214.

Bermejo P, Gamez JA and Puerta JM (2014) Speeding up incremental wrapper feature subset selection with Naive Bayes classifier. *Knowledge Based Systems* **55**, 140–147.

Breiman L (2001) Random forests. *Machine Learning* **45**, 5–32.

Burges CJC (1998) A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery* **2**, 121–167.

Cascioli V, Heusch AI and Mccarthy PW (2011) Does prolonged sitting with limited legroom affect the flexibility of a healthy subject and their perception of discomfort? *International Journal of Industrial Ergonomics* **41**, 471–480.

Ciaccia FRDA and Sznelwar LI (2012) An approach to aircraft seat comfort using interface pressure mapping. *Work* **41**, 240.

Cover T and Hart P (2003) Nearest neighbor pattern classification. *IEEE Transactions on Information Theory* **13**, 21–27.

De Looze MP, Kuijt-Evers LFM and Dieën Jaap VAN (2003) Sitting comfort and discomfort and the relationships with objective measures. *Ergonomics* **46**, 985–997.

Ellegast RP, Kraft K, Groenesteijn L, Krause F, Berger H and Vink P (2012) Comparison of four specific dynamic office chairs with a conventional office chair: impact upon muscle activation, physical activity and posture. *Applied Ergonomics* **43**, 296–307.

Fazlollahtabar H (2010) A subjective framework for seat comfort based on a heuristic multi criteria decision making technique and anthropometry. *Applied Ergonomics* **42**, 16–28.

Foubert N, McKee AM, Goubran RA and Knoefel F (2012) Lying and sitting posture recognition and transition detection using a pressure sensor array. *MeMeA 2012–2012 IEEE International Symposium on Medical Measurements and Applications Proceedings*, Budapest, pp. 1–6.

Franz M, Kamp I, Durt A and Kilincsoy Ü (2011) A light weight car seat shaped by human body contour. *International Journal of Human Factors Modelling and Simulation* **2**, 314–326.

Gao S, Zhang N, Duan GY, Yang Z and Zhang T (2010) Prediction of function changes associated with single-point protein mutations using support vector machines (SVMs). *Human Mutation* **30**, 1161–1166.

Gholipour A and Arjmand N (2016) Artificial neural networks to predict 3D spinal posture in reaching and lifting activities; applications in biomechanical models. *Journal of Biomechanics* **49**, 2946–2952.

Groenesteijn L, Ellegast RP, Keller K, Krause F and Looze MPD (2012) Office task effects on comfort and body dynamics in five dynamic office chairs. *Applied Ergonomics* **43**, 320–328.

Hales TR and Bernard BP (1996) Epidemiology of work-related musculoskeletal disorders. *Orthopedic Clinics of North America* **27**, 679.

Haller M, Richter C, Brandl P, Gross S and Inami M (2011) Finding the right way for interrupting people improving their sitting posture. *Human-Computer Interaction-Interact - IFIP TC13 International Conference.*

Hiemstra-van, S, Meyenborg I, and Hoogenhout M (2016) The influence of activities and duration on comfort and discomfort development in time of aircraft passengers. *Work* **54**, 955–961.

Huang YR and Ouyang XF (2013) Sitting posture detection and recognition using force sensor. *International Conference on Biomedical Engineering & Informatics.*

Jongryun R, Hyeong-Jun P, Kwang JL and Hyeong J (2018) Sitting posture monitoring system based on a low-cost load cell using machine learning. *Sensors* **18**, 208.

Kamiya K, Kudo M, Nonaka H and Toyama J (2008) Sitting posture analysis by pressure sensors. *International Conference on Pattern Recognition.*

Kamp I, Kilincsoy U and Vink P (2011) Chosen postures during specific sitting activities. *Ergonomics* **54**, 1029–1042.

Kolich M (2004) Predicting automobile seat comfort using a neural network. *International Journal of Industrial Ergonomics* **33**, 285–293.

Konz MRCA (2002) Leg swelling, comfort and fatigue when sitting, standing, and sit/standing. *International Journal of Industrial Ergonomics* **29**, 289–296.

Kyung G and Nussbaum MA (2013) Age-related difference in perceptual responses and interface pressure requirements for driver seat design. *Ergonomics* **56**, 1795–1805.

Lan M, Ke L and Wu C (2010) A sitting posture surveillance system based on image processing technology. *International Conference on Computer Engineering & Technology.*

Le P, Rose J, Knapik G and Marras WS (2014) Objective classification of vehicle seat discomfort. *Ergonomics* **57**, 536–544.

Lengsfeld M, Van Deursen DL, Rohlmann A, Van Deursen LL and Griss P (2000) Spinal load changes during rotatory dynamic sitting. *Clinical Biomechanics* **15**, 295–297.

Lewis L, Patel H, D'Cruz M, and Cobb S (2017) What makes a space invader? Passenger perceptions of personal space invasion in aircraft travel. *Ergonomics* **60**, 1–28.

Li YC, Wang PD, Johan G, Jen SL and Young MS (1999) The development of a distributed pressure measurement cushion to prevent bad sitting posture. *Proceedings of the First Joint BMES/EMBS Conference. 1999 IEEE Engineering in Medicine and Biology 21st Annual Conference and the 1999 Annual Fall Meeting of the Biomedical Engineering Society* (Cat. N, Atlanta, GA, USA), p. 611.

Li W, Yu S, Yang H, Pei H, Zhao C (2017) Effects of long-duration sitting with limited space on discomfort, body flexibility, and surface pressure. *International Journal of Industrial Ergonomics* **58**, 12–24.

Luttmann A, Schmidt KH and Jaeger M (2010) Working conditions, muscular activity and complaints of office workers. *International Journal of Industrial Ergonomics* **40**, 549–559.

Ma C, Li W, Gravina R and Fortino G (2017) Posture detection based on smart cushion for wheelchair users. *Sensors* **17**, 719.

Mastrigt HV, Groenesteijn L, Vink P and Kuijt-Evers LFM (2016) Predicting passenger seat comfort and discomfort on the basis of human, context and seat characteristics: a literature review. *Ergonomics* **60**, 1–44.

Meyer J, Arnrich B, Schumm J and Troster G (2010) Design and modeling of a textile pressure sensor for sitting posture classification. *IEEE Sensors Journal* **10**, 1391–1398.

Moes NCCM (2007) Variation in sitting pressure distribution and location of the points of maximum pressure with rotation of the pelvis, gender and body characteristics. *Ergonomics* **50**, 536–561.

Mota S and Picard RW (2003) Automated posture analysis for detecting learner's interest level. *Proceedings CVPR, IEEE Computer Society Conference on Computer Vision and Pattern Recognition.* IEEE Computer Society Conference on Computer Vision and Pattern Recognition 5, p. 49.

Mota S and Picard RW (2008) Automated posture analysis for detecting learner's interest level. *2003 Conference on Computer Vision and Pattern Recognition Workshop IEEE.*

Mutlu B, Krause A, Forlizzi J, Guestrin C, and Hodgins J (2007) Robust, low-cost, non-intrusive sensing and recognition of seated postures. *ACM Symposium on User Interface Software & Technology.*

Safavian SR and Landgrebe D (2002) A survey of decision tree classifier methodology. *IEEE Transactions on Systems Man & Cybernetics* **21**, 660–674.

Schrempf A, Schossleitner G, Minarik T, Haller M and Gross S (2011) Posturecare – towards a novel system for posture monitoring and guidance. *IFAC Proceedings Volumes* **44**, 593–598.

Smulders M, Berghman K, Koenraads M, Kane JA, Krishna K, Carter TK and Schultheis U (2016) Comfort and pressure distribution in a human contour shaped aircraft seat (developed with 3D scans of the human body). *Work* **54**, 1–16.

Song-Lin W and Rong-Yi C (2010) Human behavior recognition based on sitting postures. *2010 International Symposium on Computer, Communication, Control and Automation (3CA)*, Tainan, pp. 138–141.

Szeto GPY, Straker L and Raine S (2002) A field comparison of neck and shoulder postures in symptomatic and asymptomatic office workers. *Applied Ergonomics* **33**, 75–84.

Tan HZ and Ebert DS (2002) Sensing chair as an input device for human computer interaction.

Tan HZ, Slivovsky LA and Pentland A (2001) A sensing chair using pressure distribution sensors. *IEEE/ASME Transactions on Mechatronics* **6**, 261–268.

Tessendorf B, Arnrich B, Schumm J, Setz C and Troster G (2009) Unsupervised monitoring of sitting behavior. *Conference proceedings: … Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 6197–6200.

Vanacore A, Lanzotti A, Percuoco C, Capasso A and Vitolo B (2019) Design and analysis of comparative experiments to assess the (dis-)comfort of aircraft seating. *Applied Ergonomics* **76**, 155–163.

Vos GA, Congleton JJ, Moore JS, Amendola AA, Ringer L (2006) Postural versus chair design impacts upon interface pressure. *Applied Ergonomics* **37**, 619–628.

Xu L, Gang C, Wang J, Shen R and Shen Z (2012) A sensing cushion using simple pressure distribution sensors. *Multisensor Fusion & Integration for Intelligent Systems.*

Xu W, Huang MC, Amini N and He L (2013) Ecushion: a textile pressure sensor array design and calibration for sitting posture analysis. *IEEE Sensors Journal* **13**, 3926–3934.

Yoo WG, Yi CH, Kim MH (2006) Effects of a proximity-sensing feedback chair on head, shoulder, and trunk postures when working at a visual display terminal. *Journal of Occupational Rehabilitation* **16**, 631–637.

Zemp R, Taylor WR, Lorenzetti S (2015) Are pressure measurements effective in the assessment of office chair comfort/discomfort? A review. *Applied Ergonomics* **48**, 273–282.

Zemp R, Tanadini M, Plüss S, Schnüriger K, Singh NB, Taylor WR and Lorenzetti S (2016) Application of machine learning approaches for classifying sitting posture based on force and acceleration sensors. *BioMed Research International* **2016**, 1–9.

Zhu M, Martinez AM, Tan HZ (2003) Template-based recognition of static sitting postures. *Conference on Computer Vision & Pattern Recognition Workshop.*

Zubic S (2007) Sensitive chair: a force sensing chair with multimodal real-time feedback via agent. *Proceedings of the 14th European Conference on Cognitive Ergonomics: Invent! Explore!, ECCE 2007*, London, UK, August 28–31, 2007.

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