IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 23 August 2023, accepted 10 September 2023, date of publication 18 September 2023, date of current version 27 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3316693

RESEARCH ARTICLE

Comfort Wearables for In-Flight Sitting Posture Recognition

XINHE YAO[1], YUSHENG YANG[1,2], GERBERA VLEDDER[1], JUN XU[1], YU SONG[1], (Member, IEEE), AND PETER VINK[1]

[1]Faculty of Industrial Design Engineering, Delft University of Technology, 2628CE Delft, The Netherlands
[2]School of Mechatronic Engineering and Automation, Shanghai University, Shanghai 200444, China

Corresponding author: Yusheng Yang (yysshu@shu.edu.cn)

This work was supported by the European Union's Horizon 2020 ComfDemo Project under Grant 831992. The work of Xinhe Yao was supported by the China Scholarship Council under Grant 201907720095.

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Human Research Ethical Committee (HREC) of the Delft University of Technology under File No. 1228.

ABSTRACT Wearables are used to recognize human activities in various applications. However, there is limited evidence on the comfort feelings in using wearables, which is crucial for the adoption and long-term engagement of users in those applications. In this paper, we propose the concept of comfort wearables in the context of in-flight posture recognition. A comfort wearable and a tight-fit version, using identical hardware and software architecture, were prototyped and tested by 35 participants in a Boeing 737 cabin. During the usage of each wearable, participants were asked to perform seven frequently observed in-flight sitting postures and report their overall comfort/discomfort afterwards. A multilayer perceptron neural network was used to classify those activities. Experiment results indicated that participants appreciated the comfort wearable, rating it with significantly higher comfort scores and lower discomfort scores. Cross-validation results also revealed that using the comfort wearable achieved even better accuracy (74.8%) than using the tight-fit wearable (65.8%) in posture recognition. Outcomes of the study demonstrate that ergonomic design and technical accuracy are not competing factors in the wearable design and highlight the opportunities for designing and using comfort wearables in broader contexts.

INDEX TERMS Losse-fit, tight-fit, ergonomics, accelerometer, IMU, wearability.

I. INTRODUCTION

Posture recognition, as part of human activity recognition (HAR), holds a crucial role in decoding human behaviour. Its significance lies in uncovering how individuals interact with their environment during various task [1], [2]. For instance, research has shown that human body posture is one of the most important factors in determining seating comfort [3], and frequently changing of postures often indicates the development of discomfort in ergonomics studies [4], [5]. Another example is that researchers demonstrated that mental fatigue can be inferred based on body postures using the XSENS motion tracking system [6].

Human postures can be recognized based on sensors deployed in the environment. For instance, Wu et al. [7] used Intel®RealSense® to track the position of human joints and inferred hand postures accordingly. Cao and Liang [8] successfully recognized different postures of badminton players with a 90% accuracy based on captured videos and a self-developed Deep Convolutional Neural Network (DCNN). Besides cameras, pressure sensors are also frequently used in sitting posture recognition [9], [10]. In the study conducted by Wan et al. [11], 32×32 pressure sensors were placed on the top surface of the office chair cushion in a grid setup, and 12 sitting postures were recognized with an accuracy of 89.6% using Support Vector Machine (SVM). Liang et al. [12] also designed a smart cushion with pressure sensors integrated and achieved an accuracy of 98% in classifying 15 sitting postures.

The associate editor coordinating the review of this manuscript and approving it for publication was Chan Hwang See.

Though using information provided by sensors in the environment for posture recognition is effective, it is always context dependent. Using wearable sensors can mitigate this constraint [13], [14], [15]. For instance, Tian et al. [16] used data collected from a smart watch to recognize activities including standing, walking, running, upstairs, and downstairs. Fujiwara et al. [17] recognized hand postures with a mobile phone equipped on the forearm.

Many sensors can be embedded in wearables, which are worn on the body to monitor and classify different human activities in real time. For instance, Kim et al. [18] used a capacitive belt sensor placed around the fourth thoracic vertebrae to detect user daily activities with an accuracy of 74%-85%. Among different types of sensors, accelerometers and Inertia Measurement Units (IMUs, incl. accelerometers, gyroscopes and sometimes compasses) are often used in wearables for recognizing human body postures. Forsman et al. [19] found that both accelerometers and IMUs can be used to detect 4 postures and 24 types of movements based on experiments with 38 warehouse workers. Commercial products, such as XSENS [20], are often used in posture recognition. Besides, researchers also developed new types of wearables, e.g. Yan and Ou attached IMUs to the belt for fall detection [21]. Fusing information from different types of sensors might improve the accuracy, e.g. besides IMUs on the belt, Tan et al. [22] achieved an accuracy of over 98% for fall detection by integrating data from pressure sensors under the feet.

Wearables can be affixed to various parts of the human body. Depending on the level of attachment, we classify these attachment methods as either comfort/loose-fit wearables or tight-fit wearables. In tight-fit wearables, such as a smart wristwatch, the connection between the sensor and the body part remains fixed. However, in comfort wearables, such as a mobile phone in the pocket of a jacket, the attachment may not be fixed. Table 1 provides some recent studies on posture recognition utilizing different wearable designs, wherein sensors are attached to the users' torso.

The wearability [23], personalization, functionality and integration are four key factors in establishing customers' initial trust in wearables [15], [24]. The comfort of wearables, which is closely associated with wearability and personalization, can be a decisive factor in users' long-term adoption, e.g., monitoring postures of users during the day to prevent musculoskeletal disorders and improve overall health. However, as shown in Table 1, most wearables for posture recognition are tight-fit wearables and only a few are comfort wearables, e.g. Farnan et al. [25] attached 9 magnets to a comfort/loose-fit t-shirt for sitting posture recognition when working from home. Mattmann et al. [26] tried a comfort/loose-fit design with 6 ECG sensors for recognizing postures of drivers. Both studies confirmed the possibilities of using comfort wearables for posture recognition, but the accuracy was not given. The question "Is it possible to recognize postures with comfort wearables?" and "How to evaluate the comfortable feeling of wearables for posture recognition?" remain to be answered.

In this paper, we present the design and validation of a wearables, named Jacket, for posture recognition during air travel. Our scientific contributions are:

1. We developed two types of wearables, one optimized for comfort and the other for a tight-fit, utilizing identical hardware and software for inflight posture recognition.

2. Alongside accuracy, we incorporated subjective comfort ratings as a measure to evaluate the performance of the wearables.

3. We validated that properly sized comfort wearables received significantly higher comfort ratings and achieved comparable, if not slightly higher, accuracy for posture recognition compared to tight-fit wearables.

II. DESIGN OF COMFORT AND TIGHT-FIT WEARABLES

A. FRAMEWORK OF THE APPROACH

Figure 1 presents the overall approach of the study. Participants were asked to perform a set of identified postures during the flight in an aircraft seat. The tight-fit and the comfort wearables are used to collect data. The sensor configurations of the two wearables are the same: two accelerometers on the shoulders and two IMUs on the waist. The procedure of the proposed posture recognition method contains two major steps. Initially, data captured by different sensors were aligned to guarantee the inner relationship between the sensor data and the corresponding posture. Then the Multilayer Perceptron (MLP) classifier was used to predict the posture category based on the aligned sensor information.

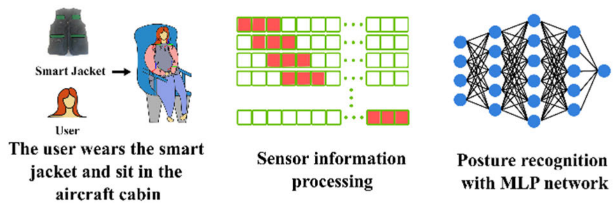


FIGURE 1. Framework of the approach.

B. HARDWARE

Figure 2 presents the block diagram of the hardware setup of the Jacket. It comprises two accelerometers (ADXL355), each capable of recording acceleration in the x, y, and z directions; two IMUs (FXOS8700 + FXAS21002), each capable of recording acceleration in the x, y, and z directions along with rotations in the yaw, roll, and pitch; a Raspberry Pi 3A+ controller; and a 3000mAH Li-polymer Battery HAT,

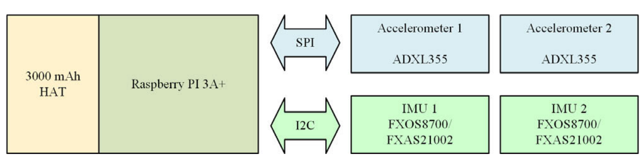


FIGURE 2. Block diagram of the hardware setup.

TABLE 1. Literature on recognizing trunk movements using wearables.

Context of the literature	Wearable Setup	Tight or Loose	No. subjects	Postures / activities	Classifier	Acc
Posturers of construction workers [27]	IMUs attached to head, chest, arm, thigh, and calf.	T	9	Overhead, bend, walk, stand.	DNN	81.2%
Postures in table tennis [28]	An IMU attached to wrist.	T	6	Hits and misses	Decision tree	95%
Sitting postures of working from home [25]	A shirt with 3*3 magnets placed above the sternum.	L	N/A	Lean left, right, forward and backward spinal postures.	N/A	N/A
Head postures [29]	Three IMUs placed around neck	T	3	Sitting: relaxing, reading book, using laptop, using mobile phone, watching videos; Standing: up, using a mobile phone; walking;	Decision extra tree	96.78%
Postures in daily activities [18]	A capacitive belt placed around chest (T4 position)	T	7	Supine with neutral head position; standing; sitting; side lying; supine with 45° cervical flexion; supine with 45° cervical extension.	Probability analysis	74%-85%
Daily sitting and standing postures[30]	IMUs at skin around the area of neck, upper back and lower back	T	7	Sit straight, back rested on chair, hands on the lap; sit straight, neck flexed down, hands on the lap; sit with rounded back, head close to table, hands on table; forward head posture, hands on able; sit deeper inside the chair, arms on the armrest, shoulder up, leg spread out; stand straight; stand with forward head posture, hands on the sides; stand swayed backwards, hands rounded in front; stand with right shoulder up, left shoulder down, body weight on right leg.	Random forest	95.68%
Swimming postures [31]	A module with IMU integrated attached to lumbar area	T	2	Different swimming styles including butterfly, breaststroke, freestyle and back crawl.	HMM	Over 90%
Posture correction and training [32]	IMU at the back of shoulder	T	4	Proper standing; proper sitting; proper exercise postures such as plank, superman, squat, side plank, etc.	N/A	N/A
Postures of daily life [33]	UCI Machine-Learning repository	N/A	4	Sitting; standing; walking; standing up; sitting down.	Random forest	Over 95%
Sitting posture monitor and correction [34]	Two IMUs at back along spine.	T	N/A	Spine bending angles	N/A	N/A
Postures of daily activities [35]	An elastic t-shirt with inductors on the front and back along spine.	T	4	Sitting on a stool, flexion-extension of the trunk; Sitting on a chair, bending-stretching forward of the trunk, hands resting on a table and return; Sitting on an armchair with trunk extended.	N/A	Correlation over 0.95
Driving postures [36]	A comfort/loose-fit t-shirt with 6 ECG sensors (2 in front along the safety belt, 4 at lower back)	L	10	Safety belt fastened: forward, on back, right, left; no seat belt: on back, others.	N/A	N/A
Postures of daily activities [26]	A tight-fit clothing with 21 strain sensors integrated into elastic textile on the back.	T	8	Sitting: upright, slumped, with rotation of trunk(right, left); bending trunk sidewards (right, left); lifting shoulders(right, left, both); arms to the front, sides and overhead; Standing: upright; with rotation of trunk(right, left); bending trunks sidewards (right, left); both shoulder lifted; slumped; bending trunk maximally forward; extending arms to the front; standing while squatted; with flexing torso sidewards (right, left).	Naive Bayes	84%

which can power the system for approximately 4 hours. A self-developed Python script was created to capture these 18 features from the four sensors at a frequency of approximately 15~30 HZ.

Using the proposed hardware, we designed comfort wearables based on a vest made of cotton denim (Fig. 3a). Two accelerometers were sewn onto the inner side of the left and right shoulders, respectively. Two IMUs were positioned around the waist, just above the two pockets. The battery was stacked on the Raspberry Pi 3A+ and positioned in the right pocket of the cotton denim. To minimize the impact of the vest on perceived comfort, soft fabric was used to cover all the wires and sensors, ensuring that users would not feel them, as shown in Fig. 3b. Twenty vests with four different sizes were created for users with varying anthropometric measures, as depicted in Fig. 3c. Sizes of the vest can be found in Table 2.

(a)The comfort wearables.

(b) A participant wears the comfort wearable (Vest size L).

(c) Comfort wearable with different sizes

FIGURE 3. Comfort wearables.

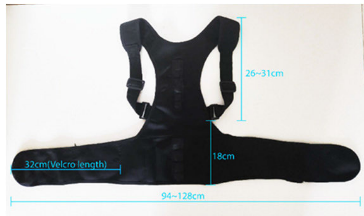
TABLE 2. Dimensions of different sizes of comfort wearables.

Size	L	XL	XXL	XXXL
Chest circumference (cm)	96	102	108	114
Length(cm)	63	64	65	66

As a comparison, we also created a tight-fit version of the wearable with the same sensors, as shown in Fig. 4. To ensure the tight fit, we designed the wearables based on an elastic undershirt, as seen in Fig. 4a. The dimensions of the undershirt were selected in such a way that it is able to fit the P5 to P95 populations due to its elasticity. Sensors are fixed onto the undershirt, as illustrated in Fig. 4b, and in Fig. 4c, a user (around P50) is shown wearing it.

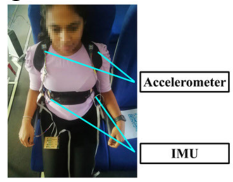
C. POSTURE CLASSIFICATION

Data $\{D_n|n = 1 \ldots N\}$ captured from 2 accelerometers and 2 IMUs were synchronized first. In this paper, $N = 18$, representing 18 features mentioned in previous section. Taking $D_n = \{D_n^{t_n^1}, D_n^{t_n^2}, \ldots, D_n^{t_n^i}, \ldots, D_n^{t_n^T}\}$ as the data of the



(a) The dimension of the tight-fit wearable.

(b) The tight-fit wearables.



(c) A participant wears the tight-fit wearable.

FIGURE 4. Tight-fit wearables.

n^{th} feature where $D_n^{t_n^i}$ means the data captured at timestamp t_n^i, we firstly down sampled all captured data to a synchronized initial timestamp T_{init} and a constant resampling frequency F_c. T_{init} was specified as:

$$T_{init} = argmax_{1 \ldots N} \left\{ t_n^1 | n = 1, 2, \ldots, 18 \right\} \tag{1}$$

and

$$F_c < argmin_{1 \ldots N} \left(F_n | n = 1, 2, \ldots, 18 \right) \tag{2}$$

where F_n is the frequency of D_n.

The resampled data for different features can be denoted as $\{DS_1, \ldots, DS_n, \ldots, DS_N\}$. Each resampled the time series data of a certain is denoted as $\left\{DS_n \,|\, DS_n = \left(DS_n^1, \cdots, DS_n^t, \cdots, DS_n^T\right)\right\}$, where

$$DS_n^t = \frac{\sum_{j=1}^{N_n^t} D_n^j}{N_n^t} \tag{3}$$

here n is the index of the feature, T is the number samples and the time interval between consecutive records $\Delta t_c = {}^1/_{F_c}$. Besides, $D_n^j = \{D_n^{t_n^i} | T_{init} + (t-1) \cdot \Delta t_c \leq t_n^i \leq (T_{init} + t \cdot \Delta t_c), \}$ N_n^t is the number of records D_n^j, as shown in Fig.5. In practice, we used 30 seconds time span for posture recognition, therefore $T = 30/\Delta t_c$.

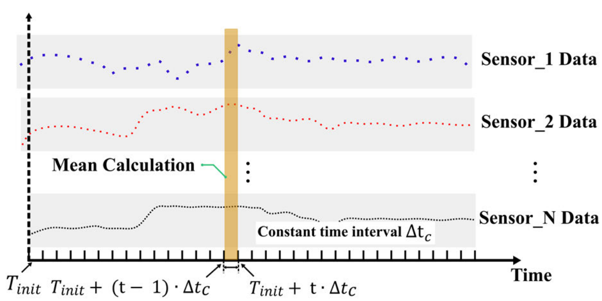


FIGURE 5. Time alignment of different sensors.

To reduce the noise in the original data, we employed the rolling window method to pre-process each DS_n as shown at the left of Fig.6. Given the aligned resampled data $\{DS_1, \ldots, DS_n, \ldots, DS_N\}$, at each timestamp t, a multi-dimension vector $\left\{s_t | s_t = \left[DS_1^t, DS_2^t, \cdots, DS_n^t, \cdots, DS_N^t\right]\right\}$ that represents all sensor features was acquired. Using the rolling window method, the output $\left\{M_t | M_t = \left(A_1^t, A_2^t, \cdots, A_n^t, \cdots, A_N^t\right)\right\}$ for posture recognition was calculated as the mean value of the data inside the window length L:

$$A_n^t = \frac{\sum_{g=1}^{N_G} s_g}{N_G} \tag{4}$$

where N_G represents the number of features of s_t between t and $(t + L)$.

MLP classifier [37] was adopted for posture recognition as shown in the right side of Fig.6. M_t was used as the input of the MLP classifier, followed by two hidden layers, each with 100 neurons. The output layer had only one node that represents the corresponding posture category. The one-vs-rest (OvR) strategy was adopted to improve prediction accuracy. For each posture, a specific MLP was trained for this category against all the other postures. Therefore, the number of MLPs for posture prediction would be the same as the number of postures to be predicted.

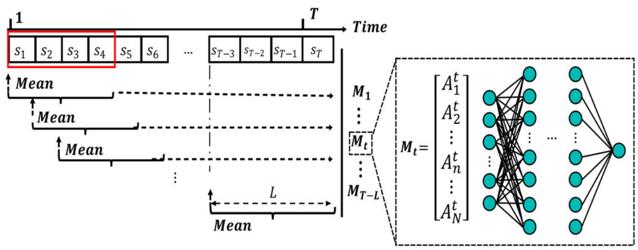


FIGURE 6. Data processing and classifier.

III. EXPERIMENT SETUP

A. POSTURE SELECTION

According to work of Liu et al. [38], the most frequently observed posture (29.7%) among passengers is sitting with the back against the backrest, both feet uncrossed on the floor and hands on the lap. Three other similar postures with different arm and head positions account for 29.1% in total. Another sitting posture mentioned as one of the most common postures is sitting straight with both feet uncrossed on the ground and hands on the lap. Slumped postures with feet/legs crossed constitute 8.8% of the observed postures. The remaining most common postures are all with the back against the backrest and feet/legs crossed. However, it was not clear which leg was on the top and which arm was performing tasks. Tan et al. [39] mentioned the body side of performing different postures in their study of sleeping postures in the economy class of an aircraft. They found that people recline to one side and use the armrest to support their body, sometimes also with rotation of their torsos so they also get support from the backrest. Using this knowledge, seven postures as Fig.7 were chosen for this study as the task for the participants.

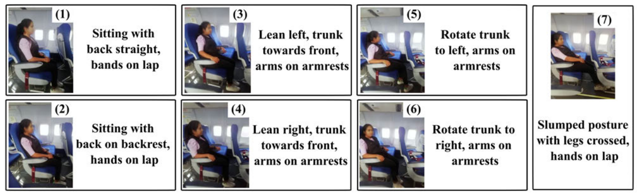


FIGURE 7. Inflight sitting postures used in this study.

B. PARTICIPANTS

To explore the use of comfort wearables for inflight sitting posture recognition, an experiment was conducted in a Boeing 737 aircraft cabin. In total 35 subjects from the Netherlands, Germany, China, India, Thailand, Italy and Brazil participated in this study. Their ages varied between 22 to 40 years old. In the experiment, participants were allowed to select the most suitable size of the comfort wearables. Detailed information about participants can be found in Table 3.

The mean height of males is 171.3 cm and for females, it is 162.7cm. As a comparison, the mean heights of the European population are 175.8 cm and 163.5 cm for men and women, respectively [40]. Regarding the sample size, G*Power calculation indicated that for medium to large effects (0.6), the sample size is able to achieve a power of 0.95. For the representativeness of the subjects in the population, the specificity [37] of the subjects in this study regarding the European population [41] is 0.002.

C. PROTOCOLS

After a short explanation and collection of consent forms, participants put on the wearables. They had about 10 minutes to get used to the wearable before the data collection started, during which they were asked to perform the postures as shown in Fig.7. Each posture took approximately 1 minute. Regarding the sequence of two types of wearables, 18 subjects started with the tight-fit wearable and the remaining participants started with the comfort wearable. After performing all the postures in a wearable, they evaluated the overall comfort and discomfort from 0 (no comfort/discomfort) to 10 (extreme comfort/discomfort) using the comfort/discomfort questionnaire [42].

IV. EXPERIMENT RESULTS

18 features on the torso movements were captured using sensors embedded in the wearable for posture prediction. The four sensors are symmetrically distributed from left to right with the zipper as the centre as Fig.8. On the left side, the features captured by the ADXL355_left were 3D accelerations. Another three acceleration features were captured by

TABLE 3. **Participant data and the size of the jacket.**

Par. No.	Age	Gender	Stature(cm)	Weight (kg)	BMI	Comfort wearable size
1	30	f	166.3	61.9	22.4	L
2	27	f	162.3	53.3	20.2	L
3	27	m	164	64.3	23.9	L
4	28	f	158.2	66.5	26.6	XXL
5	31	m	172.2	69.7	23.5	L
6	29	f	175.5	58.9	19.1	L
7	32	m	173	67.4	22.5	L
8	30	f	165.5	62.4	22.8	L
9	25	m	173	58.8	19.6	L
10	27	f	169.5	55.8	19.4	L
11	26	f	170.5	61.6	21.2	L
12	30	f	163.4	62.7	23.5	XL
13	27	m	165.7	39.1	14.2	L
14	28	f	154.5	50.8	21.3	L
15	27	f	165	53.6	19.7	L
16	34	f	159	53.8	21.3	L
17	24	m	176.5	72.1	23.1	L
18	24	m	170	67	23.2	L
19	24	m	163	58.9	22.2	L
20	26	m	167.8	64.2	22.8	L
21	40	f	160	61.1	23.9	XL
22	22	m	182.5	85	25.5	XL
23	30	m	167.5	85.8	30.6	XXXL
24	24	f	158.5	51.5	20.5	L
25	29	f	152	51.8	22.4	L
26	34	m	175.5	72.2	23.4	L
27	28	m	158	47.9	19.2	L
28	29	f	165.5	72.7	26.5	XXL
29	27	f	165.2	58.6	21.5	L
30	34	m	173.5	89.1	29.6	XXXL
31	24	f	154	57.1	24.1	XL
32	25	f	164.5	58.9	21.8	L
33	30	m	178.2	90.9	28.6	XXXL
34	24	m	179	73.9	23.1	L
35	31	m	174	70.2	23.2	L

the FXOS8700_left sensor. The features measured by the integrated FXAS2100_left sensor were 3D angular velocities. Same features were captured by the sensor on the right. Information captured by the compass was not used in this study due to: 1) the plane might turn slightly while users are sitting still; 2) there is a potential presence of products made of ferrite materials.

A. POSTURE RECOGNITION ACCURACY

Figure 9 presents the posture recognition accuracies of the comfort/loose-fit and tight-fit wearables under different sliding window widths, which were adjusted from 0.5s to 5s with a 0.5s interval. For each experiment, the network was trained and tested using the 10-fold cross-validation method, and the average prediction accuracy was taken as the result. As illustrated in Fig.9, the posture recognition accuracy based on the data captured with the comfort/loose-fit wearable was always higher than the accuracy of the tight-fit wearable. For different sliding window widths, all accuracies of using

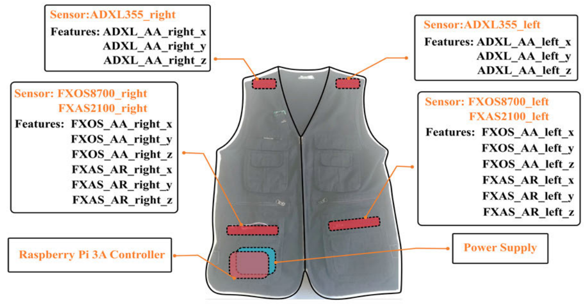


FIGURE 8. **The features captured by each sensor and the assembling position of each sensor on the comfort wearable. The same features are captured on the tight-fit wearable, and the sensors are assembled on similar positions.**

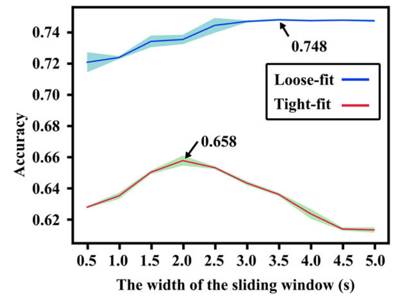


FIGURE 9. **The posture recognition accuracy of the comfort/loose-fit and tight-fit wearables with the increment of the sliding window width.**

the loose-fit wearable were higher than 72%. On the contrary, the highest accuracy of using the tight-fit wearable was about 65.8%. Overall, with the increment of the sliding window width, the accuracy of the loose-fit wearable presented an upward trend with a few fluctuations around 74% when the width was larger than 2.5s. The highest accuracy of recognition using the loose-fit wearable was 74.8% when the width of the sliding window was 3.5s.

The confusion matrix of the network with the best prediction accuracy for posture recognition with the comfort/loose-fit (74.8% accuracy when the sliding window width was 3.5s) and tight-fit wearables (65.8% accuracy when the sliding window width was 2.0s) are given in Fig.10(a) and Fig. 10 (b), respectively. The seven postures explained above are denoted as Pos1, Pos2, ..., and Pos7. For posture recognition with the loose-fit wearable, the accuracies of recognizing Pos1, Pos2, Pos4 and Pos6 reach over 80%. The lower accuracies were observed for Pos3, Pos5 and Pos7. For the tight-fit wearable, Pos1 was successively recognized with an accuracy of around 100%. Pos2, Pos3, Pos4, Pos5 can also be identified with over 70% accuracies. Low accuracy appeared in classifying Pos6 and Pos7. Nearly 56% of posture data of Pos6 was misidentified.

B. SENSOR CONTRIBUTION

18 features were used for posture recognition, and the contribution of each feature regarding the posture recognition accuracy was evaluated using the Shapley (SHAP) values [43]. Figure 11 illustrates the sorted mean SHAP value of

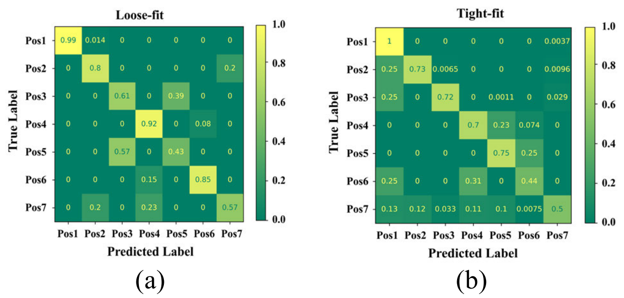


FIGURE 10. Confusion matrix of posture recognition for loose-fit (a) and tight-fit(b).

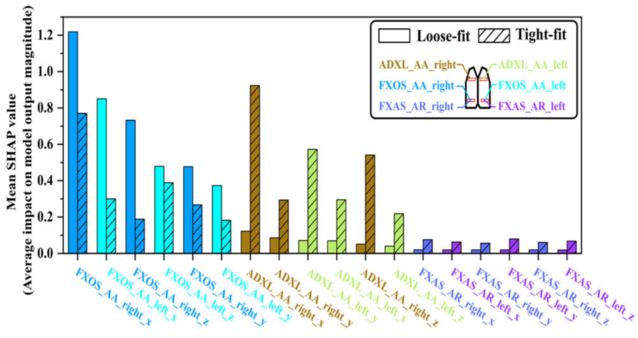


FIGURE 11. The mean SHAP value of each feature for comfort/loose-fit and tight-fit wearables.

each feature, which represents the average influence of each feature on the output of the model, for the loose-fit wearable, and the associated SHAP value for the tight-fit wearable is given as well. The accelerometer data contributed most for both the comfort/loose-fit and tight-fit wearables. It can be noticed that accelerometers on the waist (FXOS8700) contribute more than the sensors on the shoulders (ADXL355). The contribution of accelerometers on the waist and shoulders of the tight-fit wearable were nearly the same regarding the comfort/loose-fit wearable.

C. COMFORT

The comfort data from one participant was excluded due to incompleteness. The normality of both comfort and discomfort ratings was checked. Since the data were not normally distributed, Wilcoxon Rank tests were used to compare perceived comfort and discomfort regarding different versions of wearables. To understand how body shapes could influence perceived (dis) comfort wearing different versions of wearables, Pearson correlations between body measurements and (dis)comfort scores wearing different wearables were calculated. The test population was divided into two groups based on the mean value of each body measurement.

The results of the comfort and discomfort scores of the two types of wearables are presented in Table 4. The loose-fit wearable was found to be significantly more comfortable and less uncomfortable compared to the tight-fit wearable. Table 5 presents the statistically significant correlations ($p<=0.05$) between different body measurements and perceived (dis)comfort in both wearables. In the tight-fit wearable, the body weight had the largest correlation with perceived comfort, which was 0.47. The tight-fit wearable had more significant correlations between body measurements and (dis)comfort than the loose-fit wearable. Regarding different anthropometric measures, the body weight could influence both comfort and discomfort of wearing the tight-fit wearable, while height and sitting depth only affected the comfort of wearing the tight-fit wearable.

TABLE 4. Comfort and discomfort scores(0-10) of the Loose-fit wearable and the tight-fit wearable.

	Loose-fit version	Tight-fit version	P value
Comfort	4.00±1.26	3.50±1.33	0.002**
Discomfort	2.24±1.57	2.76±1.52	0.034*

TABLE 5. Correlations($p<=0.05$) between different body measurements and perceived (dis)comfort of participants wearing both comfort/loose-fit and tight-fit wearables.

	L/T fit	Age	Height	Weight	BMI	Hip width	Sitting depth	Popliteal height
Comfort	L	-	-	.40	.41	-	.42	-
Discomfort	L	.45	-	-	-	-	-	-
Comfort	T	-	.35	.47	.38	-	.42	.35
Discomfort	T	-	-	-.38	-.36	-	-	-

V. DISCUSSION

According to the findings, comfort/loose-fit wearables can achieve in-flight posture recognition with a better average accuracy than tight-fit wearables equipped with the same sensors. One possible reason for this is that the loose-fit wearable filters out noise during the data acquisition process by maintaining a small distance between the device and the human body. This distance enhancement increases recognition accuracy in certain postures, such as Pos 1 and Pos 4.

Another contributing factor is that the tight-fit wearable only achieved 44% and 50% accuracies in recognizing Pos 6 and 7, respectively, which adversely impacted its overall performance. However, both types of wearables encountered difficulties in recognizing Pos 7, the slumped position. This could be attributed to the specific cabin context of the aircraft, where subjects, especially those with a taller stature, often pressed their knees against the back of the front seats.

Moreover, postures involving rotation of the lower back posed challenges. The comfort/loose-fit wearable exhibited poor performance in detecting whether the participant's torso was rotated to the left. This could be due to the majority of participants being right-handed, resulting in greater flexibility on the right side. Consequently, the accelerometers on the shoulders, which were most effective for posture recognition during right-side rotation, significantly contributed to the performance of the comfort/loose-fit wearable.

Conversely, the tight-fit wearable exhibited less contribution to right-side torso movement, likely because the most effective sensors were located on the waist. Movement on the opposite side of the waist during body rotation might explain this observation. These distinctions highlight potential reasons for discomfort introduced by the tight-fit wearable, which constrained the movement of the subjects.

A. CLASSIFICATION METHOD

The purpose of the proposed wearables is to identify static postures, and a few large fluctuations were observed in the data. The MLP method is selected due to its simplicity rather than the long short-term memory (LSTM) method. Nevertheless, it is inevitable to encounter sensor noises and human fidgeting while seated. To address this issue, the rolling window method was employed to mitigate the noise and improve the data quality. The MLP method was also adopted by Jang et al. [44] for pose recognition based on features captured from the wearable sensors. Compared to their posture recognition accuracy of 70.1%, which was achieved based only on accelerometers, our best result was slightly better with an accuracy of 74.8% based on the comfort/loose-fit wearable.

B. POSITION OF SENSORS VS ACCURACY

Sensors were placed on the shoulders and near the waist for both the comfort/loose-fit wearable and its tight-fit version in sitting posture recognition. All the postures are common postures during flights and the variations between some postures can be very small. The required postures mainly involved thoracic and lumbar rotation, especially for Pos3, 4, 5, 6. Each vertebra is only able to rotate in a very limited range [45], e.g. Neumann indicated that the thoracic vertebra and lumbar vertebra can rotate only 3 degrees and 2 degrees respectively [46]. Besides, the contribution of accelerometers at different body parts varied between the two types of wearables. The comfort wearable relied mostly on accelerometers at the waist, while the tight-fit wearable utilized all available data in a more balanced manner. This might be caused by several reasons, e.g., in the use of comfort wearables, the friction force between the backrest and the jacket might influence the positions of the accelerometers on the shoulder, resulting in less accurate data collected at the shoulder. Meanwhile, the slightly higher accuracy of using the comfort wearables can be interpreted as that in most cases, the loose fit acts as a low pass filter regarding the movements of the human body, thus enhancing the quality of the signals.

C. WEARABLE PERFORMANCE AND COMFORT

The comfort/loose-fit wearable proved to be significantly more comfortable than the tight-fit wearable. Wearing clothing that restricts movement can be uncomfortable [47], and the comfort/loose-fit wearable allowed for more freedom of movement compared to the tight-fit wearable. Additionally, the normal appearance of the comfort/loose-fit wearable contributes to a better experience in wearing, as social pressure and others' opinions can also influence how people feel and behave when wearing different types of wearables [48].

In the experiment, participants selected the size of comfort wearables at their wish. While all users appreciate the comfort of the comfort wearables, we did not find a significant difference between size and accuracy. This addresses the importance of wearability and personalization, as personalized fit introduces a better inclusiveness for different body shapes, enabling the wider adoption of wearables in daily activities [49].

D. LIMITATION

The ages of participants in this study were limited to the range of 22 to 40, therefore the effectiveness of the proposed method on other populations, e.g., the children and the elderly, needs to be verified. Furthermore, it is important to note that although the experiment was conducted in a Boeing 737 cabin, the aircraft itself was stationary and the vibrations caused by the operating engine were not taken into consideration during the study. Additionally, the study only examined wearables with motion sensors located on the shoulders and waist, and wearables with sensors located on other parts of the body require further investigation.

VI. CONCLUSION

The study investigated the feasibility of utilizing comfort/loose-fit and tight-fit wearables for in-flight sitting posture recognition, employing an MLP-based classifier. Experiment results indicated that the comfort wearable achieved a recognition accuracy of 74.8%, surpassing the accuracy reached by the tight-fit wearable (65.8%). Furthermore, the comfort wearable was found to provide significantly higher levels of comfort and lower levels of discomfort compared to the tight-fit wearable. These findings suggest that comfort wearables can be considered as an option for posture recognition, as it reduced impact on comfort for subjects without scarifying the accuracy. Further research is needed to determine the appropriate level of looseness for different body parts in order to enhance recognition accuracy without compromising comfort.

REFERENCES

[1] H.-Y. Tang, S.-H. Tan, T.-Y. Su, C.-J. Chiang, and H.-H. Chen, "Upper body posture recognition using inertial sensors and recurrent neural networks," *Appl. Sci.*, vol. 11, no. 24, p. 12101, Dec. 2021, doi: 10.3390/APP112412101.

[2] K. Chen and Q. Wang, "Human posture recognition based on skeleton data," in *Proc. IEEE Int. Conf. Prog. Informat. Comput. (PIC)*, Dec. 2015, pp. 618–622, doi: 10.1109/PIC.2015.7489922.

[3] A. Naddeo, R. Califano, M. Vallone, A. Cicalese, C. Coccaro, F. Marcone, and E. Shullazi, "The effect of spine discomfort on the overall postural (dis)comfort," *Appl. Ergonom.*, vol. 74, pp. 194–205, Jan. 2019, doi: 10.1016/j.apergo.2018.08.025.

[4] Y. Song and P. Vink, "On the objective assessment of comfort," in *Proc. Comfort Congr.*, U. K. Nottingham, N. Mansfield, S. Frohriep, A. Naddeo, V. Peter, and A. West, Eds. Loughborough, U.K.: Chartered Institute of Ergonomics and Human Factors, 2021, pp. 1–12. [Online]. Available: https://comfort.ergonomics.org.uk/programme/#proceedings

[5] G. M. Sammonds, M. Fray, and N. J. Mansfield, "Effect of long term driving on driver discomfort and its relationship with seat fidgets and movements (SFMs)," *Appl. Ergonom.*, vol. 58, pp. 119–127, Jan. 2017, doi: 10.1016/j.apergo.2016.05.009.

[6] S. Ansari, H. Du, F. Naghdy, and D. Stirling, "Application of fully adaptive symbolic representation to driver mental fatigue detection based on body posture," in *Proc. IEEE Int. Conf. Syst., Man, Cybern. (SMC)*, Oct. 2021, pp. 1313–1318, doi: 10.1109/SMC52423.2021.9659024.

[7] Y. Wu, D.-C. Huang, W.-C. Du, M.-K. Wu, and C.-Z. Li, "Joint-based hand gesture recognition using RealSense," *J. Comput.*, vol. 31, no. 2, pp. 141–151, 2020, doi: 10.3966/199115992020043102013.

[8] P. Cao and F. Liang, "Moving posture estimation and recognition based on deep convolutional neural network," in *Proc. IEEE 3rd Eurasia Conf. IoT, Commun. Eng. (ECICE)*, Oct. 2021, pp. 298–301, doi: 10.1109/ECICE52819.2021.9645596.

[9] R. Zemp, W. R. Taylor, and S. Lorenzetti, "Seat pan and backrest pressure distribution while sitting in office chairs," *Appl. Ergonom.*, vol. 53, pp. 1–9, Mar. 2016, doi: 10.1016/j.apergo.2015.08.004.

[10] B. Mutlu, A. Krause, J. Forlizzi, C. Guestrin, and J. Hodgins, "Robust, low-cost, non-intrusive sensing and recognition of seated postures," in *Proc. Annu. ACM Symp. User Interface Softaware Technol.*, New York, NY, USA: ACM Press, 2007, pp. 149–158, doi: 10.1145/1294211.1294237.

[11] Q. Wan, H. Zhao, J. Li, and P. Xu, "Hip positioning and sitting posture recognition based on human sitting pressure image," *Sensors*, vol. 21, no. 2, p. 426, Jan. 2021, doi: 10.3390/S21020426.

[12] G. Liang, J. Cao, and X. Liu, "Smart cushion: A practical system for fine-grained sitting posture recognition," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PerCom Workshops)*, Mar. 2017, pp. 419–424, doi: 10.1109/PERCOMW.2017.7917599.

[13] H. Park, J. Pei, M. Shi, Q. Xu, and J. Fan, "Designing wearable computing devices for improved comfort and user acceptance," *Ergonomics*, vol. 62, no. 11, pp. 1474–1484, Nov. 2019, doi: 10.1080/00140139.2019.1657184.

[14] Y. Lee, D. Park, and Y. M. Kim, "The effect of wearing a head-mounted display on the boundaries of the cervical range of motion based on perceived comfort in a static posture," *Virtual Real.*, vol. 1, pp. 1–14, Sep. 2022, doi: 10.1007/S10055-022-00684-W.

[15] Y. Song, "Human digital twin, the development and impact on design," *J. Comput. Inf. Sci. Eng.*, vol. 23, no. 6, pp. 1–28, Aug. 2023, doi: 10.1115/1.4063132.

[16] D. Tian, X. Xu, Y. Tao, and X. Wang, "An improved activity recognition method based on smart watch data," in *Proc. IEEE Int. Conf. Comput. Sci. Eng. (CSE) IEEE Int. Conf. Embedded Ubiquitous Comput. (EUC)*, vol. 1, Jul. 2017, pp. 756–759, doi: 10.1109/CSE-EUC.2017.148.

[17] E. Fujiwara, M. d. S. Rodrigues, M. K. Gomes, Y. T. Wu, and C. K. Suzuki, "Identification of hand gestures using the inertial measurement unit of a smartphone: A proof-of-concept study," *IEEE Sensors J.*, vol. 21, no. 12, pp. 13916–13923, Jun. 2021, doi: 10.1109/JSEN.2021.3071669.

[18] D. G. Kim, C. Wang, J. G. Ho, S. D. Min, Y. Kim, and M.-H. Choi, "Development and feasibility test of a capacitive belt sensor for noninvasive respiration monitoring in different postures," *Smart Health*, vol. 16, May 2020, Art. no. 100106, doi: 10.1016/J.SMHL.2020.100106.

[19] M. Forsman, X. Fan, I.-M. Rhen, and C. M. Lind, "Mind the gap—Development of conversion models between accelerometer- and IMU-based measurements of arm and trunk postures and movements in warehouse work," *Appl. Ergonom.*, vol. 105, Nov. 2022, Art. no. 103841, doi: 10.1016/J.APERGO.2022.103841.

[20] Xsens. (2022). *Motion Capture*. [Online]. Available: https://www.xsens.com/motion-capture

[21] Y. Yan and Y. Ou, "Accurate fall detection by nine-axis IMU sensor," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2017, pp. 854–859, doi: 10.1109/ROBIO.2017.8324524.

[22] X. Tan, W. Jin, X. Geng, U. Wejinya, G. Shi, and W. Yan, "Human fall detection improvement based on artificial neural network and optimized zero moment point algorithms," in *Proc. IEEE Int. Conf. Real-Time Comput. Robot. (RCAR)*, Aug. 2018, pp. 662–666, doi: 10.1109/RCAR.2018.8621671.

[23] L. Francés-Morcillo, P. Morer-Camo, M. I. Rodríguez-Ferradas, and A. Cazón-Martín, "Wearable design requirements identification and evaluation," *Sensors*, vol. 20, no. 9, p. 2599, May 2020, doi: 10.3390/s20092599.

[24] Z. Gu and J. Wei, "Empirical study on initial trust of wearable devices based on product characteristics," *J. Comput. Inf. Syst.*, vol. 61, no. 6, pp. 520–528, Nov. 2021, doi: 10.1080/08874417.2020.1779150.

[25] M. Farnan, E. Dolezalek, and C.-H. Min, "Magnet integrated shirt for upper body posture detection using wearable magnetic sensors," in *Proc. IEEE Int. IoT, Electron. Mechatronics Conf. (IEMTRONICS)*, Apr. 2021, pp. 1–5, doi: 10.1109/IEMTRONICS52119.2021.9422488.

[26] C. Mattmann, O. Amft, H. Harms, G. Troster, and F. Clemens, "Recognizing upper body postures using textile strain sensors," in *Proc. 11th IEEE Int. Symp. Wearable Comput.*, Oct. 2007, pp. 29–36, doi: 10.1109/ISWC.2007.4373773.

[27] J. Zhao and E. Obonyo, "Applying incremental deep neural networks-based posture recognition model for ergonomics risk assessment in construction," *Adv. Eng. Informat.*, vol. 50, Oct. 2021, Art. no. 101374, doi: 10.1016/J.AEI.2021.101374.

[28] X. Sha, G. Wei, X. Zhang, X. Ren, S. Wang, Z. He, and Y. Zhao, "Accurate recognition of player identity and stroke performance in table tennis using a smart wristband," *IEEE Sensors J.*, vol. 21, no. 9, pp. 10923–10932, May 2021, doi: 10.1109/JSEN.2021.3060914.

[29] I. C. Severin, "The head posture system based on 3 inertial sensors and machine learning models: Offline analyze," in *Proc. 3rd Int. Seminar Res. Inf. Technol. Intell. Syst.*, 2020, pp. 672–676, Dec. 2020, doi: 10.1109/ISRITI51436.2020.9315418.

[30] R. Gupta, S. H. Gupta, A. Agarwal, P. Choudhary, N. Bansal, and S. Sen, "A wearable multisensor posture detection system," in *Proc. Int. Conf. Intell. Comput. Control Syst.*, May 2020, pp. 818–822, doi: 10.1109/ICICCS48265.2020.9121082.

[31] Z. Wang, X. Shi, J. Wang, F. Gao, J. Li, M. Guo, H. Zhao, and S. Qiu, "Swimming motion analysis and posture recognition based on wearable inertial sensors," in *Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC)*, Oct. 2019, pp. 3371–3376, doi: 10.1109/SMC.2019.8913847.

[32] M. Gan, S. M. V. Liang, A. M. M. Obciana, C. J. G. Policarpio, and H. S. Co, "Accelerometer ranges for different static postures," in *Proc. IEEE 10th Int. Conf. Humanoid, Nanotechnol., Inf. Technol., Commun. Control, Environ. Manage. (HNICEM)*, Nov. 2018, pp. 1–6, doi: 10.1109/HNICEM.2018.8666255.

[33] K. Wunderlich and E. Abdelfattah, "Human activity and posture classification using wearable accelerometer data," in *Proc. 9th IEEE Annu. Ubiquitous Comput., Electron. Mobile Commun. Conf. (UEMCON)*, Nov. 2018, pp. 77–81, doi: 10.1109/UEMCON.2018.8796831.

[34] A. Petropoulos, D. Sikeridis, and T. Antonakopoulos, "SPoMo: IMU-based real-time sitting posture monitoring," in *Proc. IEEE 7th Int. Conf. Consum. Electron.*, Sep. 2017, pp. 5–9, doi: 10.1109/ICCE-BERLIN.2017.8210574.

[35] E. Sardini, M. Serpelloni, and V. Pasqui, "Daylong sitting posture measurement with a new wearable system for at home body movement monitoring," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf.*, May 2015, pp. 652–657, doi: 10.1109/I2MTC.2015.7151345.

[36] C.-M. Yang, C.-C. Wu, C.-M. Chou, and T.-L. Yang, "Vehicle driver's ECG and sitting posture monitoring system," in *Proc. 9th Int. Conf. Inf. Technol. Appl. Biomed.*, Nov. 2009, pp. 1–4, doi: 10.1109/ITAB.2009.5394321.

[37] Y. Yang, H. Zhou, Y. Song, and P. Vink, "Identify dominant dimensions of 3D hand shapes using statistical shape model and deep neural network," *Appl. Ergonom.*, vol. 96, Oct. 2021, Art. no. 103462, doi: 10.1016/j.apergo.2021.103462.

[38] J. Liu, S. Yu, and J. Chu, "The passengers' comfort improvement by sitting activity and posture analysis in civil aircraft cabin," *Math. Problems Eng.*, vol. 2019, pp. 1–10, Dec. 2019, doi: 10.1155/2019/3278215.

[39] C. Tan, W. Chen, F. Kimman, and M. Rauterberg, "Sleeping in sitting posture analysis of economy class aircraft passenger," in *Electronic Engineering and Computing Technology* (Lecture Notes in Electrical Engineering), vol. 60. Dordrecht, The Netherlands: Springer, 2010, pp. 703–713, doi: 10.1007/978-90-481-8776-8_60.

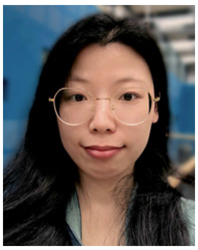
[40] S. Gallus, A. Lugo, B. Murisic, C. Bosetti, P. Boffetta, and C. La Vecchia, "Overweight and obesity in 16 European countries," *Eur. J. Nutrition*, vol. 54, no. 5, pp. 679–689, Aug. 2015, doi: 10.1007/s00394-014-0746-4.

[41] DINED. (2011). *Anthropometric Database*. Accessed: Aug. 1, 2023. [Online]. Available: http://dined.io.tudelft.nl/

[42] S. Anjani, M. Kühne, A. Naddeo, S. Frohriep, N. Mansfield, Y. Song, and P. Vink, "PCQ: Preferred comfort questionnaires for product design," *Work*, vol. 68, no. s1, pp. S19–S28, Jan. 2021, doi: 10.3233/WOR-208002.

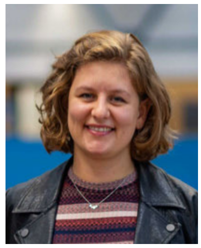
[43] S. M. Lundberg and S. I. Lee, "A unified approach to interpreting model predictions," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 4766–4775.

[44] H. K. Jang, H. Han, and S. W. Yoon, "Comprehensive monitoring of bad head and shoulder postures by wearable magnetic sensors and deep learning," *IEEE Sensors J.*, vol. 20, no. 22, pp. 13768–13775, Nov. 2020, doi: 10.1109/JSEN.2020.3004562.
[45] M. Tajdari, F. Tajdari, P. Shirzadian, A. Pawar, M. Wardak, S. Saha, C. Park, T. Huysmans, Y. Song, Y. J. Zhang, J. F. Sarwark, and W. K. Liu, "Next-generation prognosis framework for pediatric spinal deformities using bio-informed deep learning networks," *Eng. with Comput.*, vol. 38, no. 5, pp. 4061–4084, Oct. 2022, doi: 10.1007/s00366-022-01742-2.
[46] D. A. Neumann, *Kinesiology of the Musculoskeletal System, Foundations for Rehabilitation*, 3rd ed. Amsterdam, The Netherlands: Elsevier, 2016.
[47] S. P. Ashdown, "Improving body movement comfort in apparel," in *Improving Comfort in Clothing*. Philadelphia, PA, USA: Woodhead Publishing, Jan. 2011, pp. 278–302, doi: 10.1533/9780857090645.2.278.
[48] R. K. Ratner and B. E. Kahn, "The impact of private versus public consumption on variety-seeking behavior," *J. Consum. Res.*, vol. 29, no. 2, pp. 246–257, Sep. 2002, doi: 10.1086/341574.
[49] A. L. M. Minnoye, F. Tajdari, E. L. Doubrovski, J. Wu, F. Kwa, W. S. Elkhuizen, T. Huysmans, and Y. Song, "Personalized product design through digital fabrication," in *Proc. 42nd Comput. Inf. Eng. Conf. (CIE)*, Aug. 2022, pp. 1–12, doi: 10.1115/DETC2022-91173.



XINHE YAO received the master's degree from the Faculty of Industrial Design Engineering, Delft University of Technology, in 2019, where she is currently pursuing the Ph.D. degree with the Department of Sustainable Design Engineering. Her research interests include passenger comfort and physical ergonomics in aircraft cabins.

YUSHENG YANG received the Ph.D. degree from the School of Mechatronic Engineering and Automation, Shanghai University. He is currently a Postdoctoral Researcher with Shanghai University. His research interests include 3D scanning, ergonomics, and robotics.



GERBERA VLEDDER received the master's degree from the Faculty Industrial Design Engineering, Delft University of Technology, in 2017, where she is currently pursuing the Ph.D. degree. Her research interests include passenger comfort, ergonomics, acoustic comfort, sleeping in transit, and sustainable mobility.

JUN XU received the M.S. degree in biomedical engineering from Shanghai University, China, in 2018, where he started his doctor program. He is currently pursuing the Ph.D. degree with the Delft University of Technology. His current research interests include 3D printed electronics and 3D wireless power transfer.

YU (WOLF) SONG received the Ph.D. degree from the Department of Mechanical Engineering, The University of Hong Kong. He joined the Faculty of Industrial Design Engineering, Delft University of Technology, in 2001. He is currently an Associate Professor with the Department of Sustainable Design Engineering. His main research interests include human digital twin, 3D scanning, and ergonomics.

PETER VINK received the Ph.D. degree in biomechanics from the Medical Faculty, Leiden University, in 1989. He is currently a Professor of environmental ergonomics with the Faculty of Industrial Design Engineering, Delft University of Technology. His research interests include interior design, comfort and vehicle seat design and their applications in mobility. He sits on the editorial board of various scientific journals (e.g. *Applied Ergonomics*).