Analysis of Postural Variability of Office Workers Using Inertial Sensors

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Abstract: Musculoskeletal disorders significantly impact workers in terms of quality of life, result in low organisational productivity, and high insurance costs in society. Postural changes have been suggested as a prerequisite to prevent musculoskeletal disorders. This paper examines the differences in postural changes of forty office workers in a real working environment using a smartphone's inertial sensors. Through these data, several variables considered to characterise postural changes while sitting were extracted. Features based on the number of changes and different postures, time spent and distance covered within a posture showed significant differences in both time of the day (morning and afternoon) and day of the week (start and end of the week). These results confirm that accumulated working time influences a person's postural changes and could have a potential use for worker's ergonomic occupational risk evaluation.

1 INTRODUCTION

People that are part of the working population spend a significant time of their daily lives at work. Good conditions must be ensured to provide workers a safe environment in which they feel confident and where occupational risks and the onset of work-related disorders (WRDs) are kept at a minimum, contributing to productivity and economic development (World Health Organization, 2017). Exposure to risk factors such as heat, noise, and posture issues can directly contribute to causing diseases or aggravate some health conditions. Additionally, stress and some determinants at social relations at work also negatively affect workers' health (World Health Organization, 2017; Hulshof et al., 2021). Therefore, it is essential to monitor and prevent WRDs to create a safe environment and promote health at work. Strategies such as the improvement of the conception of the workplace and the education on keeping a proper posture can be very effective to reduce the risk of one of these disorders (World Health Organization, 2017; Perista et al., 2016).

Especially, occupations such as computerised office work are characterised by long-lasting low intensities, static postures, and repetitive actions (Srinivasan and Mathiassen, 2012). Consequently, different metrics and tools for measuring workers' movement have been assessed at various levels, including kinematic components and neuromuscular patterns. In healthy people, functional tasks are naturally performed with variable motor patterns, illustrating an inherited normal variation in space and time to preserve or achieve functional skills (Srinivasan and Mathiassen, 2012). Nevertheless, in the presence of musculoskeletal disorders (MSDs), people often show different motor control strategies, and changes in motor variability are often reported in kinematic parameters (e.g., reduced degrees of freedom during walking or other activities of daily living) and neuromuscular variables (e.g., reduced variability of muscle activity during repetitive lifting or other tasks) (Alsubaie et al., 2021). Thus, variation in movements, posture or muscle activity has been a prerequisite to prevent musculoskeletal complaints during functional tasks (Mingels et al., 2021).

The primary purpose of this research study is to analyse the postural changes of public administration workers in their natural work environment. The study

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focuses on sedentary work. Data were collected using the inertial sensors of a smartphone placed on the subjects' chest. This work is part of the PrevOccupAI project (Biosignals LIBPhys-UNL, 2020), which has the support of the Portuguese *Autoridade Tributária e Aduaneira* (AT) and *Direção-Geral da Saúde*. The main goal of this project is to promote occupational health and prevent WRDs, through the identification of risk factors in the office context.

2 RELATED WORK

Previous research uses several observational and data-mining techniques for occupational risk assessments. For example, Carnide et al. evaluated possible causes for MSDs through questionnaires and clinical exams, including electromyography (EMG) (Carnide et al., 2006). EMG sensors were used to compare muscle activation during computer tasks in those with and without pain in computer workers (Kelson et al., 2019) and also to quantify the spatio-temporal effects of biofeedback by inducing active and passive pauses on the trapezius activity patterns using high-density sEMG sensors in computer work (Samani et al., 2010).

Ryan and colleagues objectively investigated workplace sedentary behaviour and adherence to current recommendations via accelerometer in a population of office workers (Ryan et al., 2011). Lenzi et al. developed a toolbox to support expert video analysis of manual handling of low loads at high frequency through the use of inertial sensors (Lenzi et al., 2018).

Prior studies have used different technologies to characterise posture changes in sitting posture, such as: video analysis during laptop tasks (Mingels et al., 2021); instrumented office-chairs to explore the relation to the development of perceived discomfort (Søndergaard et al., 2010) and detect the difference between ages (Madeleine et al., 2021); textile pressure mat to observe the characteristics of movement patterns during a prolonged sitting bout and to determine their association with musculoskeletal pain (Arippa et al., 2022) and other concerning problems such as back pain in office workers (Bontrup et al., 2019); motion analysis system to quantify the self-reported discomfort in a stool, a computer chair, and a gaming chair (Chen et al., 2021) during sustained office work via wireless inertial motion sensors (Jun et al., 2019).

The mentioned studies all focus on using highly specialised equipment that are often expensive. In this paper we aim at utilising equipment that is available to all workers without extra costs by using a smartphone placed on the subjects' chest as a data acquisition tool. Furthermore, to the best of our knowledge, there are no studies that explore the evolution of postural changes in office workers through the smartphone's inertial sensors.

3 DATASET

3.1 Participants

The acquisition sessions were performed with office workers from AT, working in a real-world scenario at their own workplace. The participants performed their regular office work, and each participant was monitored while working for five consecutive days, sitting at their desk.

These sessions took place at four different AT divisions and in four different weeks. There were a total of 40 participants, 10 for each AT division. The participants' age was 51 ± 5 years and the overall body mass index was 25.34 ± 4.40 kg/m^2, 24.78 ± 4.79 kg/m^2 for females (n = 27) and 26.71 ± 3.03 kg/m^2 for males (n = 11).

3.2 Experimental Setup

The study was conducted in order to collect inertial data from people working at their desks. A smartphone was placed on the chest of each participant, using a special strap around the neck and torso, according to Figure 1. This configuration ensured that the smartphone's y-axis was pointing up.

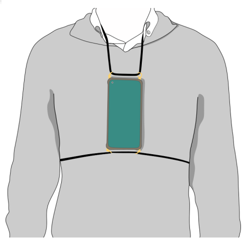

Figure 1: Smartphone placement for data acquisition.

The smartphones used are Xiaomi Redmi Note 9 models (Xiaomi Inc., www.mi.com), which include a variety of sensors, such as accelerometer, gyroscope, magnetometer, and rotation vector.

Using the PrevOccupAI mobile application (Silva et al., 2022), a total of four acquisitions were scheduled for each of the five days. These included two acquisitions in the morning and two in the afternoon, to allow an analysis of the acquired signals throughout the day and the week. The sampling rate was set to 100 Hz and the acquisition time to 20 minutes.

Thus, while participants were working, the acquisitions started and ended automatically.

4 METHODS

4.1 Data Pre-Processing

The smartphone runs the Android operating system, which is designed to prioritise battery saving. That can lead to the sensors starting at different times, sampling asynchronously, and using a non-equidistant sampling procedure. Hence, the acquired sensors of a device become misaligned in time and therefore it is necessary to resample all signals to the same equidistant sampling rate and crop them to the same size. As the acquisitions included accelerometer, gyroscope, magnetometer, and rotation vector, the procedure was done for all of them so that their signals could be analysed simultaneously.

The first step is to define the starting and stopping points, and crop or pad the signals according to that. For this work, we chose the starting point as the initial timestamp of the last sensor that started acquiring, and the stopping point as the final timestamp of the first sensor that stopped acquiring. The differences between the starting and stopping times of the sensors usually do not exceed a couple of seconds.

After cropping, each signal has to be individually resampled, to assure that the sampling frequency is constant and the same for all sensors. Therefore, a new time axis with constant intervals was generated, beginning and ending at the defined starting and stopping points, respectively. Then, each signal was individually interpolated, using the new time axis. This way, the smartphone sensors data were finally aligned. The new sampling rate was set to 100 Hz and a linear interpolation was performed.

4.2 Removal of Non-Sitting Periods

As acquisitions were performed in a real-world scenario, it is possible that the participants did not remain seated for the entire acquisition period.

To ensure the validity of the analysis to be performed, it was important to develop an algorithm to detect the periods when a participant was not seated and remove these from the data. For this purpose, we performed some additional acquisitions of a person sitting and walking (using the same setting) and trained a machine learning model which detects when a participant is not seated. This model is based on the random forest algorithm and reached an accuracy of 100% using a 70/30% split with five different seeds.

To apply this machine learning model, the smartphone's accelerometer signals were first filtered using a smoothing filter with a Hanning window of 30 samples. Then, the signals were divided into windows of 5 seconds and both statistical and temporal features were extracted from each signal window. Using these features, each window was classified by the model as *sitting* or *walking*. Finally, the windows classified as *walking* were removed from the signals to analyse. This way, the variables related to postural variability while sitting could be extracted.

4.3 Extraction of Postural Variables

After pre-processing, we defined a set of variables that we considered representative of postural variability. This postural variability refers to the adjustments each person makes to their sitting posture. Posture is defined as the position where we keep our body when we are seated. The considered variables include:

- Number of changes in posture;
- Number of different postures;
- Mean time of transition between postures;
- Time spent in each of the subject's three most common postures;
- Time spent in the remaining postures;
- Total distance covered;
- Distance covered in each of the subject's three most common postures;
- Distance covered in the remaining postures;
- Variance in each of the subject's three most common postures;
- Mean variance in the remaining postures;
- Mean velocity;
- Mean velocity in each of the subject's three most common postures;
- Mean velocity in the remaining postures.

To extract these variables from the available data, we used the smartphone's rotation vector, which allows the calculation of the subject's trunk position at each moment. The rotation vector sensor merges accelerometer, gyroscope, and magnetometer data, and is based on the mathematical concept of quaternions, which is the description of 3D orientation using a 4D complex number system (Goldman, 2011). Thus, the smartphone's rotation vector returns four values that describe the phone's orientation relative to the phone's base coordinate system, which is illustrated in Figure 2.

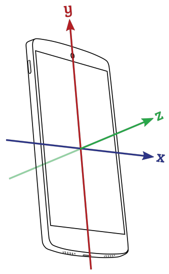

Figure 2: Coordinate system of the smartphone.

These quaternions were first converted to Euler angles, and the median was subtracted and considered as the reference point. The Euler angles were then transformed into positions in the xz-plane (according to Figure 2), which corresponds to the horizontal plane when the subjects have the phone placed on their chest. The x and z coordinates allow the determination of the inclination of the trunk in that plane, at a given moment, which defines the different postures of each person. To allow the comparison of postures between subjects, these coordinates were normalised by the height of each individual.

Furthermore, it was also necessary to categorise the different possible postures into finite ranges. Taking into account that the obtained x and z coordinates ranged from -1 to 1, the xz-plane was divided into a grid of equal squares (7x7), whose dimensions were manually chosen to optimise the number of different postures, as represented in Figure 3. The grid was equally distributed in both directions, consisting of 49 different possible postures. However, some of those 49 intervals are humanly impossible to reach.

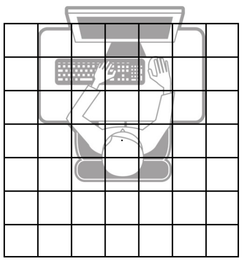

Figure 3: Division of the xz-plane to define the possible postures.

Moreover, some of the extracted variables required the implementation of additional preprocessing tools. To extract the variables not involving variability within the same posture (number of changes in posture, number of different postures, mean time of transition between postures, time spent in each of the subject's three most common postures, and time spent in the remaining postures), the postural sway behaviour was removed. This behaviour corresponds to the small and unconscious movements around the body's center of mass needed to maintain balance while standing or sitting (Paterno et al., 2013). This postural sway, if not removed, can cause oscillations between the limits of two of the defined postures, affecting the extracted variables. These small oscillations are unconscious and do not involve changes in posture, as they are only adjustments that each individual makes to their posture. For this reason, to extract some of the variables, the higher frequencies were removed from the signals by applying a low-pass filter with a cut-off frequency of 0.3 Hz (Soames and Atha, 1982) to the Euler angles.

To allow comparison between subjects, some of the 21 variables had to be normalised. The number of changes in posture was normalised by an hour, while some of the variables involving time (time spent in the most common, second most common, third most common, and remaining postures) and the variables involving distance (total distance and distance covered in the most common, second most common, third most common, and remaining postures) were normalised by the time of acquisition (approximately 20 minutes).

4.4 Analysis of Postural Variables

From the four acquisitions per day, for the purpose of this study, we extracted the first in the morning of the first day, the last in the afternoon of the first day, the first in the morning of the fifth day, and the last in the afternoon of the fifth day (4 out of the 20 acquisitions of each subject). Thus, the statistical analysis allows to evidence the evolution of each variable throughout the day and throughout the week.

A two-way repeated measures analysis of variance (ANOVA) test was applied to each dependent variable considering as levels the time points of the day (morning and afternoon) and days of the week (first and fifth). The p-values were corrected by the Greenhouse-Geisser method. Normality assumption was considered under the Central Limit Theorem and the level of significance was set to 5%.

5 RESULTS

Table 1 presents the results of the two-way repeated measures ANOVA for time of the day (*Time*) and day of the week (*Day*), and their respective interaction. Figure 4 displays the evolution of the mean values of the variables that showed statistically significant differences and/or significant interaction according to Table 1.

Table 1: Statistical analysis of the extracted postural variables by two-way repeated measures ANOVA.

Variable	Comparison (Time)	Comparison (Day)	Interaction (Time × Day)
Number of changes in posture	0.014*	0.004*	0.274
Number of different postures	0.010*	0.011*	0.468
Mean time of transition between postures	0.761	0.066	0.396
Time spent in the most common posture	0.002*	0.154	0.423
Time spent in the second most common posture	0.351	0.927	0.152
Time spent in the third most common posture	0.067	0.776	0.595
Time spent in the remaining postures	0.001*	0.008*	0.631
Total distance covered	0.330	0.000*	0.799
Distance covered in the most common posture	0.074	0.017*	0.152
Distance covered in the second most common posture	0.936	0.935	0.386
Distance covered in the third most common posture	0.861	0.793	0.181
Distance covered in the remaining postures	0.001*	0.002*	0.089
Variance in the most common posture	0.022*	0.846	0.950
Variance in the second most common posture	0.752	0.017*	0.305
Variance in the third most common posture	0.088	0.085	0.080
Mean variance in the remaining postures	0.056	0.118	0.655
Mean velocity	0.657	0.003*	0.104
Mean velocity in the most common posture	0.171	0.177	0.369
Mean velocity in the second most common posture	0.895	0.029*	0.805
Mean velocity in the third most common posture	0.074	0.425	0.433
Mean velocity in the remaining postures	0.069	0.029*	0.027*

*p-value significant at $\alpha = 0.05$ level.

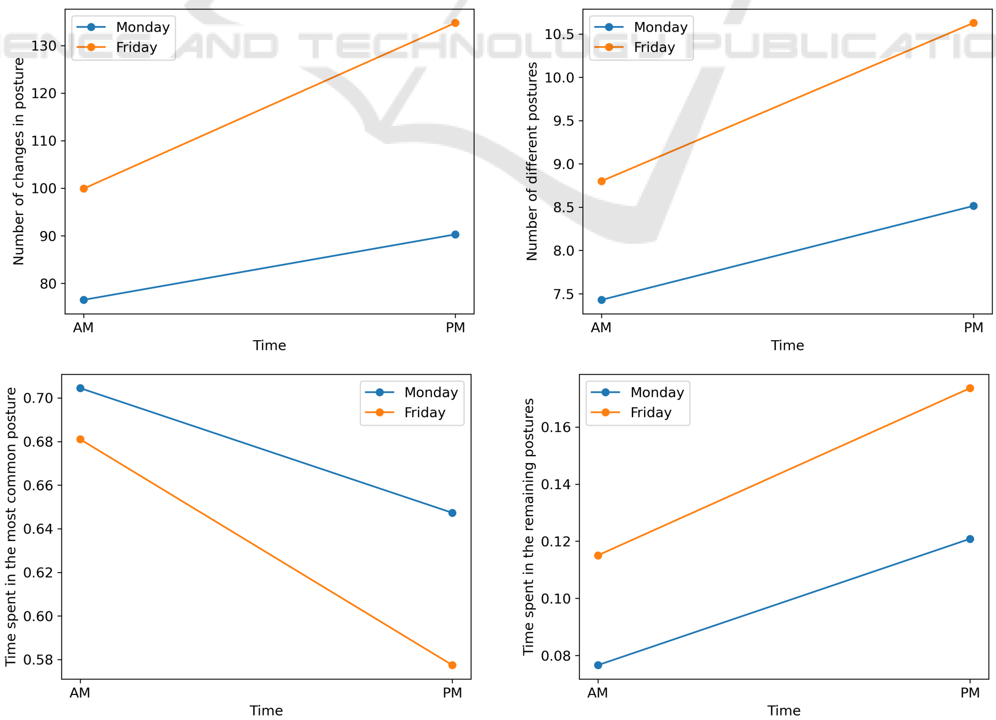

Figure 4: Evolution of the variables' mean values throughout the day and throughout the week.

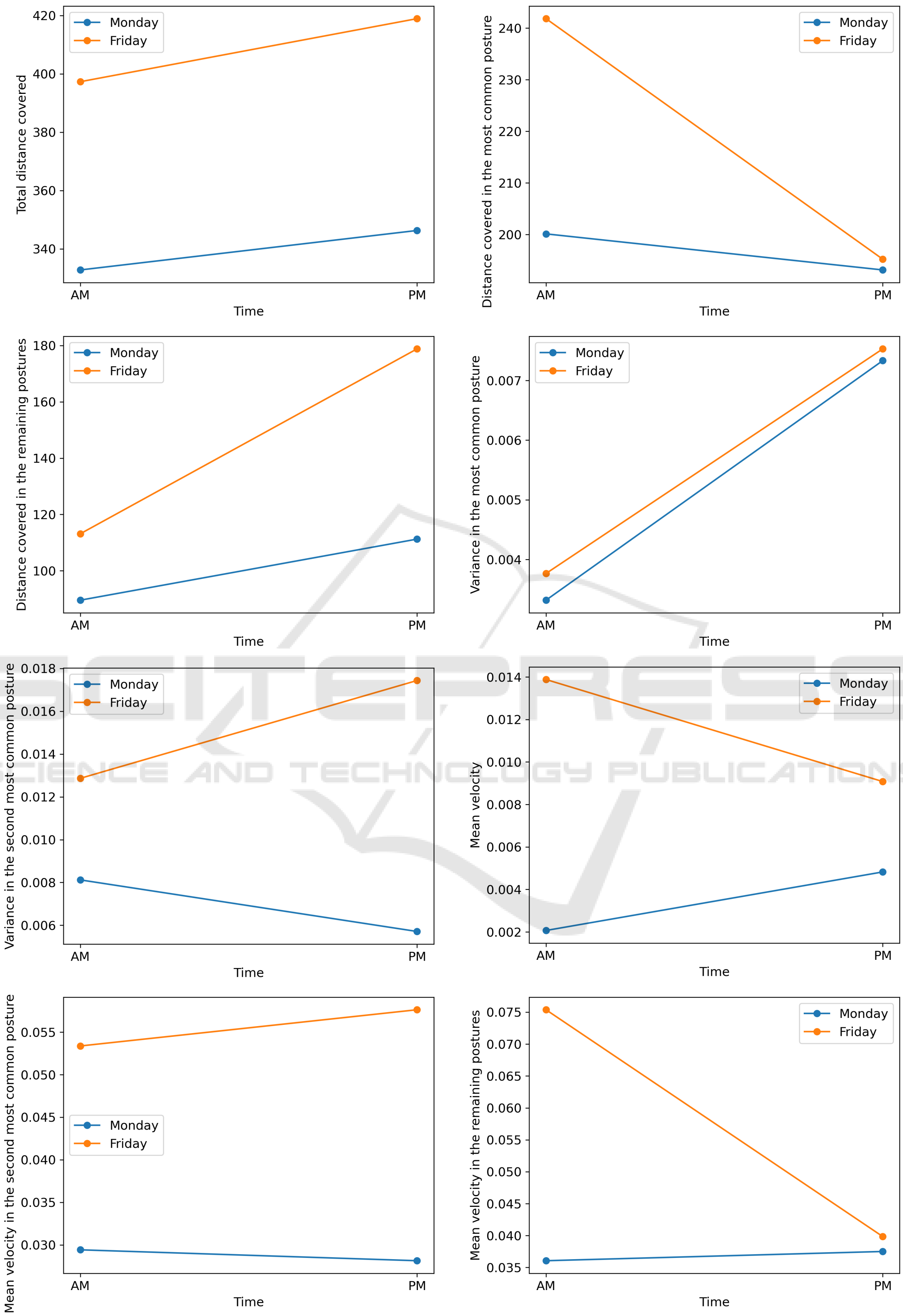

Figure 4: Evolution of the variables' mean values throughout the day and throughout the week (cont.).

6 DISCUSSION

The current investigation evaluated the postural variability of public administration workers in a seated posture, through variables extracted from the smartphone's rotation vector sensor, which was placed on the subjects' chest. As the acquisitions were carried out during a working week for each participant, it was possible to study the evolution of postural changes throughout the day and week.

Regarding the different periods of the day (morning and afternoon), shown in Table 1, 6 out of the 21 variables present significant differences between the two time periods. These include the number of changes in posture, number of different postures, and time spent in the most common posture. Taking into account Figure 4, it can be seen that the number of changes in posture and number of different postures increase from the morning to the afternoon, while the time spent in the most common posture decreases from the morning to the afternoon. These results are in accordance with the literature, which demonstrates a need to change posture throughout the working day (Søndergaard et al., 2010; Jorgensen et al., 2012; Son, 2017; Forsman et al., 2007). This is due to the fact that long periods of sitting lead to increased discomfort, which makes people move more and change their posture (Søndergaard et al., 2010). This means that postural variability (changes) tends to increase throughout the day, as a strategy to resist accumulated tiredness and discomfort.

Concerning different days of the week (Monday and Friday), Table 1 shows that 10 out of the 21 variables present significant differences between the first and fifth days. These, in addition to including the number of changes in posture and number of different postures, also include some variables related to distance (total distance covered, distance covered in the most common posture, and distance covered in the remaining postures). Figure 4 shows that all these 5 mentioned variables present an increase from Monday to Friday. This is because the subjects also accumulate fatigue throughout the week, increasing their general movement and postural variability. This accumulation of tiredness is more noticeable throughout the week than throughout the day, as evidenced by the number of variables that show significant differences.

Finally, Table 1 also shows that interaction between the independent variables *Time* and *Day* was not statistically significant for 20 out of 21 postural variables. These results demonstrate that the relationship between time of the day and each of the postural variables is not influenced by the day of the week, and also that the relationship between day of the week and each of the postural variables is not influenced by the time of the day. This reinforces the validity of the measurements performed.

7 CONCLUSION

In this work, we analysed the postural variability of office workers through inertial smartphone data collected in real context. For this purpose, we performed a 40-subject study with public administration workers performing office work. From the collected data, 21 variables characterising postural changes while sitting were extracted.

The postural variables were statistically analysed to understand their evolution during a work day and a week. Some of the variables presented statistically significant differences between the morning and the afternoon, but the first and fifth days presented more variables with significant differences. These results evidence the accumulated fatigue throughout the day and the week. Regarding interaction between the independent variables, only one postural variable presented interaction between the variables *Time* and *Day*.

The results obtained can be used as a means to help assign a degree of ergonomic occupational risk to each subject, which can be employed to build a tool that automatically assesses the occupational risk of a worker. This risk may then be used to make recommendations to office workers, such as short standing breaks or changes in posture.

In the future, to ensure the validity of the analysis performed, it is important to extend the study to more subjects, and to collect data over more working days. Additionally, the set of participants should include more diverse age groups, and potentially different working populations, including workers who do not work in public administration. Furthermore, postural variables that encompass time series variability in postural sway using nonlinear analysis should be considered.

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