Carmen Cecilia Espinoza Melo
(Organizadora)

Avanços e Desafios da Inteligência Artificial

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PRÓLOGO

Vivimos un tiempo en que la Inteligencia Artificial (IA) ha dejado de ser un horizonte tecnológico para convertirse en un eje central de las transformaciones sociales, culturales y científicas a escala global.

Más que una innovación, la IA constituye hoy un terreno fértil de debates, investigaciones y aplicaciones, que se extienden desde la educación básica hasta los tribunales de justicia, desde la vida cotidiana en salud hasta la protección de los derechos humanos. Este libro, *Avances y Desafíos de la Inteligencia Artificial*, reúne contribuciones de académicos de distintos países que, desde perspectivas diversas, examinan los caminos, las posibilidades y también los riesgos asociados al uso de esta tecnología.

La obra se organiza en tres ejes temáticos que reflejan la complejidad híbrida de las tecnologías emergentes: **Educación y Aprendizaje; Sociedad y Salud; y Derecho y Ética**. Este marco invita a una lectura transversal e interdisciplinaria.

En el **primer eje, Inteligencia Artificial en la Educación y el Aprendizaje**, los capítulos analizan cómo la IA está transformando los procesos formativos en distintos niveles educativos. Se presentan experiencias con chatbots y aplicaciones móviles, la integración de herramientas como *Magic School AI* y sistemas de gestión del aprendizaje, así como reflexiones sobre el impacto de la IA en la motivación estudiantil, el rol docente y la personalización de la enseñanza.

El **segundo eje, Inteligencia Artificial, Sociedad y Salud**, dirige la mirada hacia la vida cotidiana. Un estudio experimental sobre la relación entre actividad física diaria y calidad del sueño, apoyado en dispositivos de monitoreo, ilustra tanto las oportunidades que abre la analítica de datos como las tensiones metodológicas y éticas de trabajar con información sensible y heterogénea. Este apartado invita a repensar el vínculo entre IA, bienestar y responsabilidad social en el manejo de datos.

En el **tercer eje, Derecho, Ética e Inteligencia Artificial**, se concentran las discusiones más críticas sobre los dilemas que la IA plantea a la sociedad contemporánea. Los capítulos examinan los derechos humanos de cuarta generación y la necesidad de resguardar principios éticos en la Cuarta Revolución Industrial. Se analizan también los desafíos que enfrenta el sistema judicial frente a la automatización y la toma de decisiones algorítmica, subrayando cómo la IA puede tensionar los fundamentos mismos de la justicia, la legitimidad institucional y el compromiso democrático.

En conjunto, estos nueve capítulos reafirman que la Inteligencia Artificial no es únicamente un campo técnico, sino, ante todo, humano: depende de nuestras decisiones, de nuestra ética y de la capacidad de diálogo entre disciplinas.

Así, este libro es más que un compendio académico: constituye una invitación a la reflexión crítica, a la cooperación interdisciplinaria y a la construcción de futuros en los que la tecnología esté al servicio de la dignidad, el aprendizaje y la vida en sociedad.

Que cada capítulo despierte preguntas, inspire diálogos y contribuya a ampliar la comprensión crítica sobre los rumbos de la Inteligencia Artificial en nuestras sociedades.

Carmen Cecilia Espinoza Melo

SUMÁRIO

CAPÍTULO 6

CAUSALITY BETWEEN DAYTIME MOTOR ACTIVITY AND SLEEP QUALITY

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ABSTRACT: Among the data that can be collected by the most common wearable health devices, the number of steps taken and the quality of the user's sleep are very recurrent. There is a logical, rational, and subjective belief that there is a relationship between these two indicators. This paper investigates the relationship between these variables of interest using statistical and experimental methods. Health devices were used to collect data from different individuals. A paired samples t-test was used to determine whether there was a statistically significant difference between the means of two related groups. As a final result, it was concluded from the data analyzed that this relationship could not be ruled out, with challenges in data analysis due to the heterogeneity of the devices used and the irregular participation of the subjects in their observation tasks.

KEYWORDS: daytime motor activity; health devices; sleep quality; paired observations.

1. INTRODUCTION

In recent years, since the remote working has produced serious imbalances in our daily activities and sleep patterns, the relationship between those two factors is a topic of high relevance for health professionals [5]. It is crucial to keep studying each factor separately. There is huge evidence of the direct relation between the daily activity and a wide range of medical conditions like obesity [4] and psychological problems.

Professionals states that the lack of daily activity can lead to more dangerous health problem: cardiovascular disease, diabetes among others. In the other side, the quality of sleep is the most important indicator for the mood. An inappropriate period of sleeping can cause concentration, reaction, stress and productivity problems. It causes also difficulties in the learning process for students. The significance of sleep in maintaining optimal health and cognitive function is undeniable. A proper quality of sleep not only allows the body to recover energy but also fortifies the immune system. However, beyond the consequences of each factor separately, the relation between them raise as new topic in order to find new evidence and improve the treatments for certain clinical conditions. For materialize this relation, those factors need to be analyzed together.

Analyzing the sleep quality and daily activity was a challenge some years ago, However, nowadays there are plenty of technological tools that can monitor them. Regarding tracking the daily activity, the smartphone stands out as the predominant instrument employed for this task. Its non-intrusive nature aligns seamlessly with the daily routines of nearly all users, who habitually carry their smartphones. There are hundreds of free mobile applications used for tracking daily activities e.g: walking, running, cycling, etc. [6]. Furthermore, the accuracy of the measures can improve by using wearable devices, e.g: smartwatches (used the most), smart glasses, smart clothing, etc. In most of the cases, those devices need to be connected via Bluetooth to an smartphone. The aim of those devices is recording the activities with high accuracy and their usage is invasive. By the other side, for tracking the sleep quality the smartwatches are widely used [3]. While several mobile applications are available for recording sleep patterns, the majority of them are not offered free of charge. Invariably, to pursue the primary objective of analyzing these factors, it becomes imperative for users to maintain an internet connection, as the data necessitates processing.

Although any device is able to record trusty data, remarkable variance and diversity are noted among the data recorded across user. Each one present a unique profile of daily activity and sleep patterns. There are certain exogenous variables omitted from the recorded data that nonetheless exert a substantial influence on any analysis or research endeavor (e.g.: sex, health condition, season, weather, etc.). It underscores the critical necessity of addressing healthcare in a personalized manner. Traditional approaches show significant limitations in accurate understanding of health conditions and effectiveness of interventions [2]. Therefore, new approaches and treatments are leaning towards strategies that incorporate individual analyses [10].

The wearable devices have garnered significant interest due to their potential to continuously monitor health data [8]. However, this technology has some handicaps which limit its usage. First, those devices are seen as invasive as they requires to be en touch with the body of the user. It makes them very uncomfortable and this is one reason for the user to stop using it (even when their use is recommended by medical professionals). In addition, they need battery and internet connection. This can be an obstacle in environments where these resources are not guaranteed. Finally, the economic cost associated with acquiring it can also mean a significant barrier, as many of them require a considerable investment from the user.

The current paper extends the findings outlined in the previous work [9], within the scope of the ongoing investigation under the ACERTA project [1].

The primary objective of this article is to leverage data gathered from wearable devices and smartphones to establish a causal relationship between daily activity and sleep quality. Through meticulous analysis of this data, our goal is to identify patterns which indicates how physical activity and other daily habits directly influence the duration and depth of sleep. By this article we not only want produce scientific evidence related the relationship between daily activity and sleep quality, but also provide knowledge in order to improve clinical treatments.

2. METHODOLOGY

After describing the initial data, the methodological steps taken to obtain the results are identified.

2.1. DATA

The data used in this study were gathered from volunteer users who took part in this project [1]. They used smartwatches from the brands Withings and FitBit. The available dataset spans from 2016 to 2023; however, observations containing data on both variables (daily activity and sleep quality) commence from 2018 onwards. Those devices record several variables, however most of them were discarded because we want to focus in the daily activity and the sleep variables only.

Since data comes from different devices, it comes in different formats. Figure 1 reveals a notable disparity in the raw data structure between the Withings and Fitbit datasets. The data from Withings is presented in a condensed form, comprising solely two columns denoting date and value, aggregated by date. Conversely, the Fitbit dataset offers a more granular representation, with data disaggregated hourly. As a consequence of this disparity, an integration process was necessitated. [7].

Figure 1: Raw data from several devices.

(a) Steps done from Fitbit device.

```
Id,ActivityHour,StepTotal
1503960366,4/12/2016 12:00:00 AM,373
1503960366,4/12/2016 1:00:00 AM,160
1503960366,4/12/2016 2:00:00 AM,151
1503960366,4/12/2016 3:00:00 AM,0
1503960366,4/12/2016 4:00:00 AM,0
```

(b) Sleep actvity from Fitbit device.

```
de,a,"from (manual)","to (manual)",Timezone,"Activity type",Data,
2018-04-14T20:26:00+02:00,2018-04-14T20:51:00+02:00,,,Europe/Madr
2018-04-17T12:56:00+02:00,2018-04-17T13:11:00+02:00,,,Europe/Madr
2018-04-17T19:42:00+02:00,2018-04-17T19:59:00+02:00,,,Europe/Madr
2018-04-19T13:47:00+02:00,2018-04-19T14:06:00+02:00,,,Europe/Madr
2018-04-19T15:30:00+02:00,2018-04-19T15:47:00+02:00,,,Europe/Madr
```

(C) Steps done from Withings device.

```
date,value
2018-11-26,4385
2018-11-25,0
2018-11-24,0
2018-11-23,64
```

(d) Sleep actvity from Withings device.

```
de,a,"from (manual)","to (manual)",Timezone,"Activity type",Data,
2018-04-14T20:26:00+02:00,2018-04-14T20:51:00+02:00,,,Europe/Madr
2018-04-17T12:56:00+02:00,2018-04-17T13:11:00+02:00,,,Europe/Madr
2018-04-17T19:42:00+02:00,2018-04-17T19:59:00+02:00,,,Europe/Madr
2018-04-19T13:47:00+02:00,2018-04-19T14:06:00+02:00,,,Europe/Madr
2018-04-19T15:30:00+02:00,2018-04-19T15:47:00+02:00,,,Europe/Madr
```

In relation to daily activity, the devices recorded variables like swimming time, running time, riding time among others, however those variables did not give enough information because those activities were not performed continuously. On the con-trary, the steps done is a variable which was recorded regularly in the time for any user. We used this variable in our study.

Regarding to sleep, some devices recorded variables like the number of times of wake-up at night, total time of no-sleeping time at night, REM phase time among others. Some devices added the sleep quality as a continuous variable, others do not. But in any device, two variables were always included: the sleep time and the wake- up time. We took advantage of those variables for calculate our own sleep quality variable. For the scope of this study, we considered the sleep quality as time between the sleep time and wake-up time normalized in a scaled variable from 0 to 1.

2.2. DATA PROCESSING SYSTEM

The ranges of the study variables are checked using the data described in section 2. Since daytime motor activity and sleep quality are variables of different magnitudes, they must first be normalized to conduct a consistent study.

We need to make sure that both variables are paired because we want to show causality between steps and sleep quality. The pairing we applied is: the sleep quality from a night was paired with the steps done at the next day. Therefore, for a specific date and patient, we had the sleep quality and steps done as variables to analyze. We used those variables to built our integrated dataset whose detail can be observed in table 1.

Before to proceed with a consistent study, there was only one remaining issued that need to be fixed: for analysis and visualization purposes, we need the variables to be normalized in the same scale. The sleep quality was already scaled between 0 to 1, however the steps done had a very high variance and we need to scale it in the same way. Therefore, we used the min-max strategy applied over the steps done for each user. A sample of the resulting dataset can be observed in table 2. This table serves as the starting point for subsequent analysis.

Table 1: Variables in integrated dataset.

Variable	Type	Description	Example
Dataset	Character	Name of the source dataset	DS031
Device	Character	Name of the devices which recorded the data	WITX3.1
Date	Date	Date of the observation	04-04-2018
Patient	Character	User identification	user01
Sleep quality	Numeric	Customize sleep quality	0.78
Steps done	Numeric	Steps done at day	3204

Table 2: Normalised variables' example.

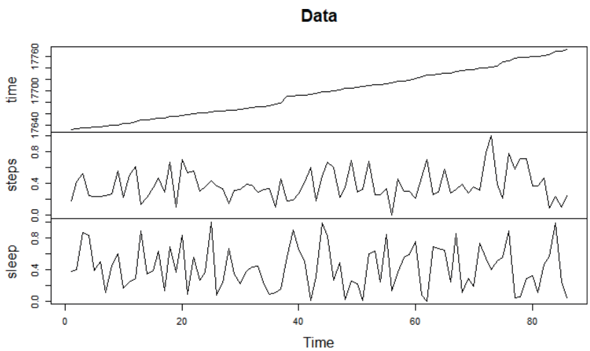
Datas	eDt evice	Date	User	Sleep Quality	Steps done
DS03	1WITX3.	04-04-2018	user0	10.78	0.53
DS03	1WITX3.	05-04-2018	user0	10.63	0.59
DS03	1WITX3.	06-04-2018	user0	10.73	0.76
DS03	1WITX3.	07-04-2018	user0	10.70	0.86

2.3. DATA ANALYSIS METHODS

We have two main variables to focus on: *steps* and *sleep* which, once normalized, show no Pearson neither Spearman, nor Kendall correlation.

Visualizing the variables concerned shows that there is no obvious correlation, as indicated by the numerical methods used. In Fig. 2 there are the variables *steps*, *sleep*, and a timeline are shown. This indicates that the samples have been taken on contiguous dates and followed in time, making it easier to visually compare working variables.

Figure 2: One of the samples' standardized survey data.



The fact that the Pearson correlation coefficient is close to zero, although the other coefficients show no significant differences in interpretation, suggests that there is no significant linear relationship between the number of steps taken and sleep quality in the data set analyzed. In other words, increasing or decreasing the number of steps taken does not seem to be systematically associated with an improvement or decrease in sleep quality, as far as the study of the correlation between the number of steps taken and sleep quality is concerned.

However, it is important to note that a correlation close to zero does not necessarily mean that there is no relationship between the variables, but rather that the relationship between them is not linear. Furthermore, Pearson's correlation does not imply causality, so no conclusions about cause and effect can be drawn from this value in this case study.

Based on the above, it does not seem reasonable to use linear models to describe a possible relationship between steps and sleep quality, nor is it possible to use polynomial regression, as there is no apparent curvilinear relationship between the variables.

After the exclusion of a linear relationship between the variables, our studies focus on the causality of the two indicators to prove causality between the variables *steps* and *sleep*, it is necessary to carry out a more in-depth analysis that goes beyond correlation.

In research, especially in observational and clinical studies, it is essential to distinguish between correlation and causation. Correlation indicates a statistical relationship between two variables but does not necessarily imply that one variable is the cause of the other. To explore causality, a more rigorous analysis is required, such as hypothesis testing, which can provide stronger evidence of a causal relationship between two continuous independent variables.

The variables *steps* and *sleep* could be considered paired if each observation of one variable is paired with an observation of the other variable in the same subject, as in our case. In this paper, each day (or subject) has a value for both *steps* and *sleep*, making these variables paired.

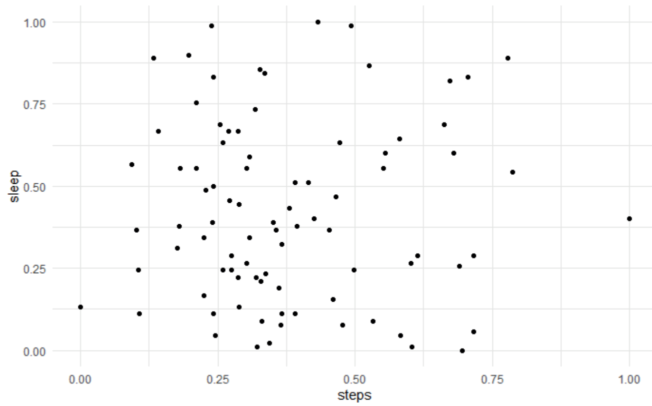
The use of paired variables can increase the precision of statistical analyses by controlling for between-subject variability. By comparing paired observations, any effects due to individual differences are canceled out, which can make the results more accurate and reliable. This may allow a more accurate and sensitive analysis of the relationship between *steps* and *sleep*.

Having justified all the above aspects for this research, it was decided to subject the samples to a hypothesis test that would in any case provide a likely scenario to argue causality on the working dataset.

Before choosing a particular test, there are aspects to consider:

- Variable independence; It is examined whether the joint probability distribution is equal to the product of the marginal probabilities. In this paper, we decide whether to accept that the variables *steps* and *sleep* are independent. Based on an independence test by formulating a $\chi 2$. As there are expected frequencies of less than 5. The p-value of the test $\chi 2$ of independence using simulations is more appropriate. As a result, we obtain increasing values of the p-value, higher than 0.6028794, and above the significance level, which allows us to accept the hypothesis that the variables are independent. The scatter diagram may be examined in Fig. 3.

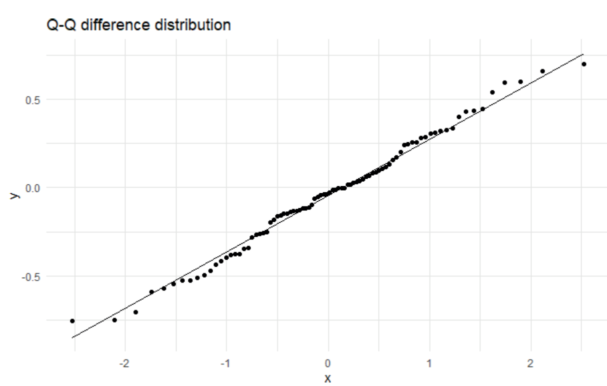
Figure 3: Scatter diagram steps-sleep.



- Normality of difference distribution; The most common test for paired variables shows greater efficiency when the difference between the variables under study retains a normal distribution. In this particular case, the variables are *steps* minus *sleep*.

The Shapiro-Wilk test is the statistical test used to determine whether the sample of data differences follows a normal distribution. This test produces a result that does not allow the null hypothesis to be rejected, a p-value of 0.7119, indicating that there is insufficient evidence to say that the data are not normally distributed. A Q-Q plot is also used to check data normality, which is a common assumption in many statistical methods. If the data follow a normal distribution, the points on the Q-Q plot will line up approximately in a straight line, as can be seen in Fig. 4, the central part of the line is highly aligned, while it weakens a little at the ends.

Figure 4: Difference distribution. Q-Q plot.



2.4. DATA VISUALIZATIONS

In research that starts with datasets that seem to have variables that are difficult to relate, it is essential to use visual tools to help us understand the goal we are trying to achieve.

The histogram of the study variables concerning the time at which they were obtained is shown in Fig. 2. This graph is part of the work with time series, but it was also used to present the results of this report. Otherwise, we have not worked exclusively with time series.

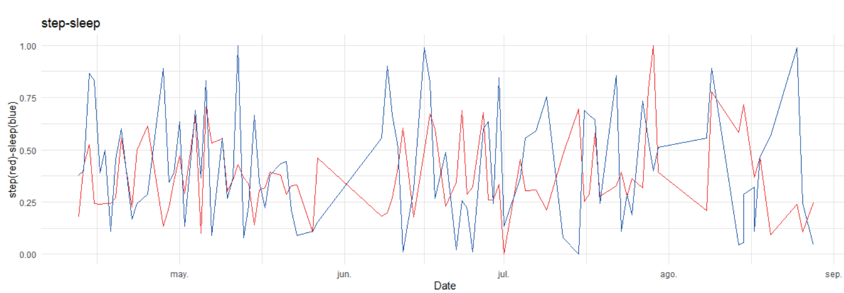
In addition, the use of the scatterplot allowed us to visually confirm the lack of apparent relationship between *steps* and *sleep*, as shown in Fig. 3 below.

It is common to test the normality of variables, which is demonstrated qualitatively by testing hypotheses of normality. But visually it can be contrasted with a quantile-quantile plot, as in Fig. 4, which is a graphical tool used to compare the probability distribution of a sample of data with a theoretical distribution.

In addition to the aforementioned techniques, the usability that other data visualization techniques can bring to this work is remarkable. They are detailed below.

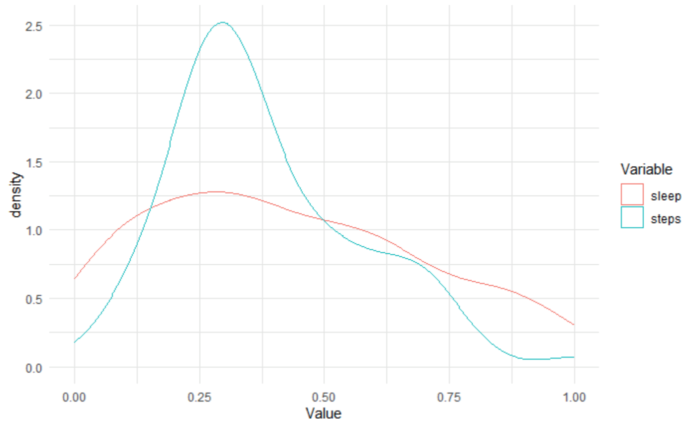
- Overlap histograms; used on the *step* rate and *sleep* variables may be useful to compare distributions. And in this particular case, to verify that the higher the rate of *step*, the higher the rate of *sleep*. This could be an existing indication of the causality that we are investigating. It can also be used to identify patterns, detect outliers, and even assess normality. The applicability of this graph to the study can be seen in Fig. 5.

Figure 5: Overlapping steps-sleep.



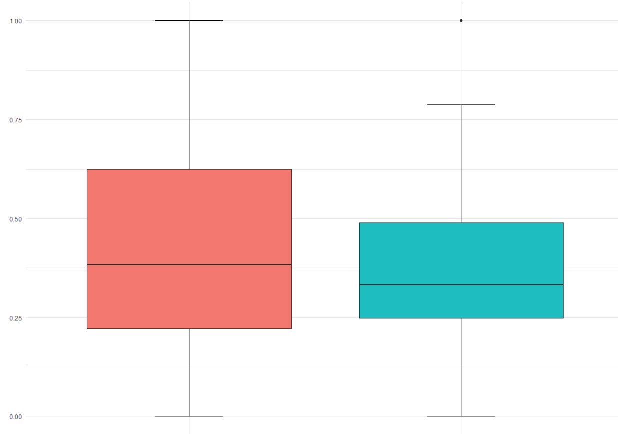
- Density plots; allow the probability distribution of the data to be visualised. In our case study, a density plot is useful to understand how the data is distributed for each variable and to compare the distributions and identify relationships between them. It is also used to test for normality. The applicability of this graph to the study can be seen in Fig. 6.

Figure 6: Density plot steps-sleep.



- Box plot; data visualization tool that allows summarising and graphically representing the main characteristics of a data distribution. In the case of the variables *steps* and *sleep*. A box plot is useful for summarising key statistics, identifying outliers, comparing distributions, and identifying relationships between variables. The applicability of this graph to the study can be seen in Fig. 7, where we can see that the range of the variables is normalized between 0 and 1, and although the variable *sleep* maintains its data spread over the whole range, this does not happen in the variable *steps*, although one outlier is observed. On the other hand, the interquartile range of *sleep* is wider, although the medians are fairly even.

Figure 7: Boxplot steps-sleep.



Working with data is not limited to quantitative methods, but visualization tools have been used to additionally squeeze all the information that can be extracted from it.

3. RESULTS

Having developed some basic premises in section 2.3, it is time to develop a hypothesis that does not rule out causality between the variables studied in this paper.

To do this, we will focus on a paired t-test. This test is robust to the assumption of normality, especially with large sample sizes. The independence of observations is a key assumption, while equality of variances is not assumed in the paired samples t-test.

To perform this test we must calculate the mean of the differences between paired observations $\overline{D}$, the standard deviation of these differences sD, and know the number of observations n. With these data, we can calculate the value of the t-statistic:

$$t = \frac{\overline{D}}{\frac{sD}{\sqrt{n}}}$$

The key point is the hypothesis statement, which in our case will state the null hypothesis $H0$ that the mean difference is equal to zero ($\overline{D} = 0$), indicating that there is no significant difference between the means of the two measurements. The alternative hypothesis $H1$ is that the mean difference is not zero ($\overline{D} \neq 0$), indicating that there is a significant difference between the means.

Closer to our case study, $H0$ means that there is no statistically significant difference between the daytime motor activity index and the sleep quality index. Both variables may be causal. While $H1$ means that there is a statistically significant difference in the activity index.

The paired t-test gives a high p-value of 0.2305 or a 23.05% probability of obtaining a result at least as extreme as the one observed. In addition, the type II error (β) calculated for the experiment was: 0.004346777 for a sample of 86 observations.

A significance level of 0.05 has been used, so the null hypothesis ($H0$) is not rejected. This means that there is not enough evidence to conclude that there is a significant difference between the means of the two variables.

Additional tests included Cohen's d and the Wilcox test, all of which produced results in the same direction.

A high p-value does not prove that the null hypothesis is true, it only indicates that the observed data are consistent with that hypothesis. Furthermore, the p-value is only one measure of evidence and must be interpreted in the context of the study and combination with other measures and analyses.

Although the paired samples t-test can indicate whether there is a significant difference between the means of the two measurements, it cannot by itself establish a causal relationship between the variables. To establish causality, controlled experiments have been conducted to observe the effect of changing one variable on the other over time. In this case, it is demonstrated using a quantitative method that the hypothesis put forward as the objective of this paper cannot be discarded. And that the experimental evidence is consistent with the results obtained.

4. CONCLUSIONS

The exhaustive study of the independent variables allows us to determine using a paired samples t-test; a statistical method that is robust to the assumption of normality and that, due to the nature of the paired design, does not require equality of variances. Be able to adjust to the objectives of this work.

The hypothesis of no difference between the variables, which would imply a possible causal relationship, has a high calculated p-value, indicating a probability of observing the data if the hypothesis were true. This leads us not to reject the hypothesis. There is insufficient evidence to confirm the existence of a significant difference between *steps* and *sleep*.

However, serious difficulties were encountered in analyzing the data collected, such as the heterogeneity of the teams and the lack of regularity of the subject carrying out the observations. For this reason, we propose to continue this line of research by increasing the segregation of the observations by providing master indicators such as age groups, sexes, times when the motor activity is performed, the type of main motor activity performed, and even the times. of food intake and the calories provided in each intake. These ranges facilitate comparison between groups.

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