

## Article

# Global Impact of COVID-19 Pandemic on Physical Activity Habits of Competitive Runners: an Analysis of Wearable Device Data

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**Abstract:** The COVID-19 pandemic resulted in government restrictions that altered the lifestyle of people worldwide. Studying the impact of these restrictions on exercise behaviors will improve our understanding of environmental factors that influence individuals' PA. We conducted a retrospective analysis using an index of government pandemic stringency developed by Oxford and a wearable device for runners to compare strictness of lockdowns and exercise habits, using digitally-logged PA data from more than 7,000 runners on a global scale. Additionally, time-of-day of PA globally and levels of PA in 14 countries are compared between the pre-pandemic year of 2019 and the first pandemic year of 2020. We found that during the pandemic the time-of-day that people exercised experienced a major shift, with significantly more activities logged during standard working hours on workdays ( $p < 0.001$ ) and fewer during the same time frame on weekends ( $p < 0.001$ ). Of the countries examined, Italy and Spain had among the most strict lockdowns and suffered the largest decreases in activity counts, whereas France experienced a minimal decrease in activity counts despite enacting a similarly strict lockdown. This study suggests that there are several factors affecting PA, including government policy, workplace policy, and cultural norms.

**Keywords:** wearable device, physical activity, behavior, COVID-19, pandemic, exercise habits, analysis, objectively measured physical activity



**Citation:** Romero, J.L.; Lv, Q. Global Impact of COVID-19 Pandemic on Physical Activity Habits of Competitive Runners: an Analysis of Wearable Device Data. 2022, 1, 0. <https://doi.org/>

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## 1. Introduction

The COVID-19 pandemic impacted the lives and well-being of people worldwide. Early in 2020, the COVID-19 pandemic disrupted the normal lifestyle of people around the world, due to government-issued lockdowns which required people to spend significant time sheltering inside their homes. Countries instituted stay-at-home orders that included transitioning from traditional in-person schooling and work to remote modalities, travel bans, non-essential workplace closures, and restricting public gatherings. Restrictions caused social isolation, affecting mental and physical health [1]. There is evidence that the psychological impact of the pandemic was strongly negative and lasted throughout the entirety of the 2020 pandemic year and continued to decline even after the pandemic was brought under better control [2]. Additionally, there is concern that the sustained loss of routine and access to exercise might have resulted in an increase in sedentary behavior [3]. The number of people working from home increased greatly, and previous work has shown that those who commute report significantly greater PA than those who do not, even without significant difference in recreational PA [4,5].

Physical activity (PA) provides a range of benefits for overall well-being including alleviating stress and depression, maintaining a healthy body composition, improving sleep quality, and mitigating certain types of disease. Investigating the impact of the pandemic on physical activity behavior could provide valuable information for researchers, public health officials, policymakers, and employers to better understand and promote healthy PA during the remainder of this pandemic, future pandemics, and during normal, pandemic-free

times. Furthermore, this pandemic provided an unprecedented opportunity to use sensing technology not available in previous pandemics to collect data on how people responded to conditions caused by the pandemic. This large-scale digital data on exercise habits holds potential to elucidate the policy, environmental, and personal influences that drive healthy lifestyle choices [3,6].

A majority of previous research on PA during the COVID-19 pandemic found that PA was generally decreased [7,8]. These studies used a variety of data sources including survey questionnaires, digital step-counts, and internet search trends, and have yielded inconclusive insights into PA during the pandemic, due to the heterogeneity of data sources, types of PA tracked (i.e., step-counts, active minutes, intensity of exercise), and subject population [7,8]. Stockwell *et al.* published a systematic review in early 2021 on the changes in PA from before to during the COVID-19 pandemic; they reported that 45 papers were found to report PA in healthy adults during COVID-19, with only four of these papers reported device-based measures and the rest based on questionnaires [7]. Most research on PA uses self-reported survey data, which is unreliable and subject to recall bias compared with objectively-measured activity data [7,9,10]; furthermore, subjects are more likely to over or underestimate their PA when self-reporting [11,12] and studies with large populations may show significant relationships than true [11]. Detailed interpretation of PA from questionnaires are discouraged [11]. Objectively-tracked PA data is more sensitive than surveying [11] and thus the literature highlights the need for more research based on objective measures in order to provide direct accurate comparisons [7,8,11,12]. There remains a large gap between questionnaire-based studies and objective studies using activity tracking devices.

Studies using smartphone activity-tracking data found that both step-counts and active time decreased during the 2-3 months following initial lockdowns [13,14]. While this research indicates that step-counts may have decreased, big data analysis suggest an increase in other measures of PA [15–18]. Fitbit, a large wearable device company, reported that overall steps were down from 2019 to 2020, however, active minutes increased for 42% of Fitbit users from 2019 to 2020 [17]. Strava, a leading exercise-recording platform that reached 73 million users in 2020, reported that from 2019 to 2020 global activity counts increased 33% and global outdoor running activities increased 90% [18]. In summary, while multiple sources of data suggest that step-counts declined, big data analysis from wearable device platforms suggests that people were logging dedicated exercise efforts more frequently than prior to the pandemic, perhaps in an effort to compensate for reduced daily-steps.

There are several studies examining a particular country's exercise habits during initial lockdown periods [13,19,20]; or evaluating exercise habits of particular groups like disabled adults [21,22], older adults [23], working parents [24]; or using survey data to compare between habitually active and infrequent exercisers, [25,26]. Ding *et al.* reports survey results spanning 11 countries and 11,775 subjects, showing that residents of countries with more stringent COVID-19 response policies were more likely to be insufficiently active according to public health recommendations [20]. While these studies are useful for understanding PA in particular groups, there is limited research directed at investigating governmental pandemic policies and physical activity across multiple countries. Research leveraging large objective datasets will help provide a more comprehensive understanding of PA during the COVID-19 pandemic.

In this work, we conduct an exploratory data analysis of wearable device data recorded internationally over a two-year period including a pre-pandemic year (2019) and a pandemic year (2020), using data obtained from the running wearable device company Stryd<sup>1</sup>. Our work includes descriptive and statistical analyses and elucidates the PA behaviors of dedicated runners, including time of exercise and activity levels, and compares them between years, countries, and severity of government COVID-19 containment policies.

<sup>1</sup> www.stryd.com

Specific contributions of this work include the following:

- This work employs objective activity-tracking data from a wearable device to provide a direct comparison of exercise behavior between a pre-pandemic year and a COVID-19 pandemic year.
- We elucidate how PA changes in dedicated runners at the country level and provide descriptive comparison between countries and pre-pandemic to pandemic years.
- We show that from the pre-pandemic to the pandemic year there were several large and significant shifts in the time of day that runners log activity, and we break these patterns down by country.
- Our work examines specific countries' government policy timelines coupled with physical activity behaviors of dedicated runners. Previous research lacks comparison between governmental pandemic policies and objectively-tracked physical activity across multiple countries.
- Stryd data is a source of highly detailed training data for runners worldwide. Our work offers insights into the exercise behavior of active individuals who are runners. We provide the first academic analysis of user exercise behavior of this commercial wearables dataset.

## 2. Materials and Methods

### *Description of Wearable Device*

Running activity data was provided by the company Stryd, which markets a footpod for runners and maintains an online analytics dashboard and smartphone application for users to track their training. The Stryd footpod attaches to shoelaces and can be connected via Bluetooth to a smartphone or fitness watch.

Stryd's footpod is not used for continuous daily tracking; it is used only for in-run tracking. Stryd's footpod costs \$219 in early 2020 and is marketed towards dedicated runners with an interest in technically-detailed fitness data. Due to its price-point and marketing, Stryd users tend to be dedicated amateur runners, competitive runners, college, semi-professional, and professional runners, or triathletes. As such, running is likely to be among the highest priority types of exercise for these users.

### *Data Cleaning*

We obtained anonymized data collected from November 1, 2018 through January 1, 2021 according to Coordinated Universal Time (UTC). All activities represent runs and include fields such as unique user IDs, timestamps, distance traveled, elapsed time during the activity, average speed, local temperature, and starting GPS coordinates. Some activities lack GPS coordinates due to setting configurations or if performed on a treadmill. Initial cleaning was performed, including dropping rows without valid IDs or with blank usernames.

For our analysis, only users who had logged a run on or prior to January 3rd, 2019 (UTC) were kept, all others were dropped. Near world-record caliber activities were dropped (0.78% of activities), defined as having average speeds exceeding 11m/s, max speed exceeding 12m/s, or having a combination of individual activity distance greater than 5000m with an average speed greater than 6.4m/s.

GPS coordinates were used to map activities to country and time zone with the Python packages `timezonefinder` and `reversegeocode`. Timestamps were converted from UTC time zone to the local time zone. 18.3% of 2019 activities and 0.7% of 2020 activities were without GPS data, due to advances in the Stryd platform's compatibility and also perhaps due to decreased indoor exercise during COVID-19. To handle this difference in the number of activities lacking GPS data between 2019 and 2020, non-GPS runs were assigned to the country and time-zone where the majority of the individual's runs with GPS data took place. Users without a single majority country over the two years and users with different majority countries between 2019 and 2020 were dropped from the analysis.

Users who had logged at least one activity before January 3rd, 2019 and at least 20 activities in each of 2019 and 2020 were included. After the cleaning steps, over 7,000 unique users remained in our dataset. The number of users within the 14 countries that we analyzed ranges from over 90 users to over 2,000 users.

### *Analysis of Exercise Behaviors*

#### Activity Counts

In this paper, activity counts are defined as the number of activities recorded in Stryd's database. We examine activity counts for different time periods and countries.

#### Government Policy Strictness

Government policy strictness was quantified using Oxford's Government Response Stringency Index (GRSI), a time-series government policy strictness index for individual countries capturing the harshness of several virus containment strategies including school, workplace, and public transport closures, cancellations of public events and gathering restrictions, stay-at-home requirements, restrictions on internal and international travel, and public information campaigns [27]. The GRSI is on a scale of 0 to 100, with 0 indicating a lack of pandemic policy, and can be directly compared across countries. Our analysis employs the GRSI in order to explore physical activity changes in the pandemic year that correspond with major policy changes.

#### Activity Counts by Country

We selected 14 countries that are highly represented in our dataset. First, we examine total activity counts by year and country. The World Health Organization (WHO) declared COVID-19 as a global pandemic on March 11, 2020. To control for seasonality, we compare and report the change in activity counts from 2019 to 2020 using the 67-day periods before and after March 11. Since 2020 is a leap year, we remove February 29 data from the analysis to keep the length of the time periods equal. We also plot the distribution of the number of activities logged in a year by each user, broken down by country and pre-pandemic and pandemic year.

We also conduct a time-series analysis of activity counts. We reported normalized activity counts by day and country. Normalized activity counts were calculated by dividing the number of activities that day in the given country by the number of users in the country. This normalization allows activity counts to be compared between countries, since the number of users differed in each country. Finally, a 14-day rolling average was applied to the activity counts to smooth out variations due to weather and weekday.

#### Time of Day That Athletes Run

Time of day of activities was calculated using GPS coordinates to identify the respective time zones and extract local time. To examine pandemic-related behavior, we restricted this analysis to data recorded after March 11th in both years, since March 11, 2020 was the WHO pandemic declaration date.

Activities were partitioned into one-hour bins for each hour of a 7-day week. Activity counts were normalized by dividing each bin activity count by the largest bin activity count. Then, the difference in activity counts in 2019 and 2020 were plotted for each bin.

Next, we defined three time periods: before work (12 AM to 8 AM), during standard working hours (8 AM to 5 PM), and after work (5 PM to 12 AM). These time periods are limited in that they do not represent all job types. Activity counts for each time period on each day were calculated then normalized equally by dividing by the largest bin size.

We hypothesized that the mass shift to working- and schooling-from-home provided more schedule flexibility. We conducted 2-tailed student's t-tests paired by user to test for the difference between mean activity counts per time bin per day between 2019 and 2020. A test is conducted individually for each of the time bins on each day, comparing the binned

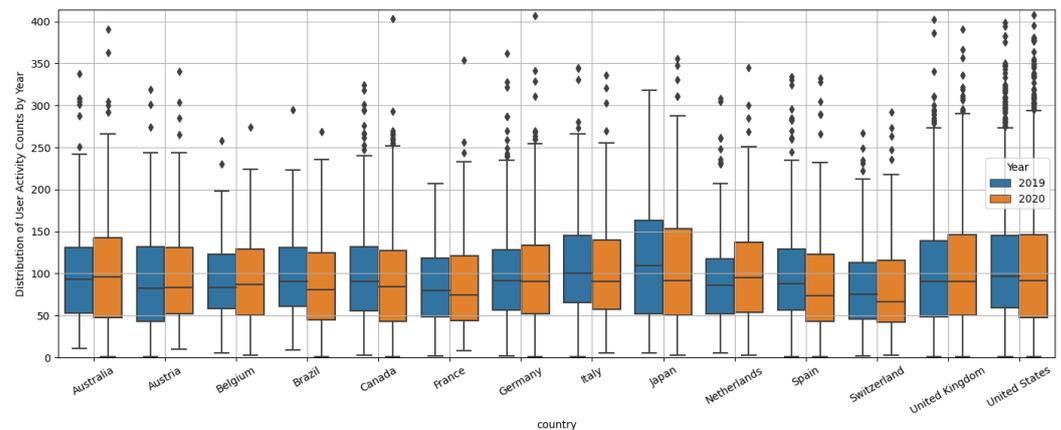
activity counts of each user between years. This test is also conducted for each of the 14 selected countries, individually. We use Python's SciPy package for this statistical analysis.

### 3. Results

#### *Exercise Habits by Country and Government Response*

##### Activity Frequency by Country

There were 4.11% fewer activities logged in 2020 than in 2019 for all countries in aggregate. Figure 1 shows a comparison between country and year of user activity counts. There is variation across countries in how the median and interquartile range of activity count per user changes from the pre-pandemic to pandemic year, with 8 countries having a decreased median, 3 countries having an increased median, and the others having a very similar median. Similarly, most countries had an increased interquartile range, suggesting that PA behavior of users diverged during the pandemic. Figure 2 shows the difference in activity counts from 2019 to 2020 for 14 countries, corresponding to the two 67-day periods before and after March 11, the date the WHO declared a pandemic. This data is tabulated in Supplementary File 1 (Table S1). The countries with the largest decrease in activity between before and after March 11 are Spain, Italy, and Brazil, all with decreases larger than 14%. This decrease indicates that PA of residents of these countries may have been more greatly affected by the pandemic and that these countries' lockdown policies may be detrimental to maintaining PA. Six of the 14 countries had decreased activity counts in the period after March 11 compared with before March 11, while the other eight countries had increased counts. The countries with the greatest increase were Switzerland, Netherlands, and United Kingdom, each having more than a 5% increase from the period before to the period after March 11.

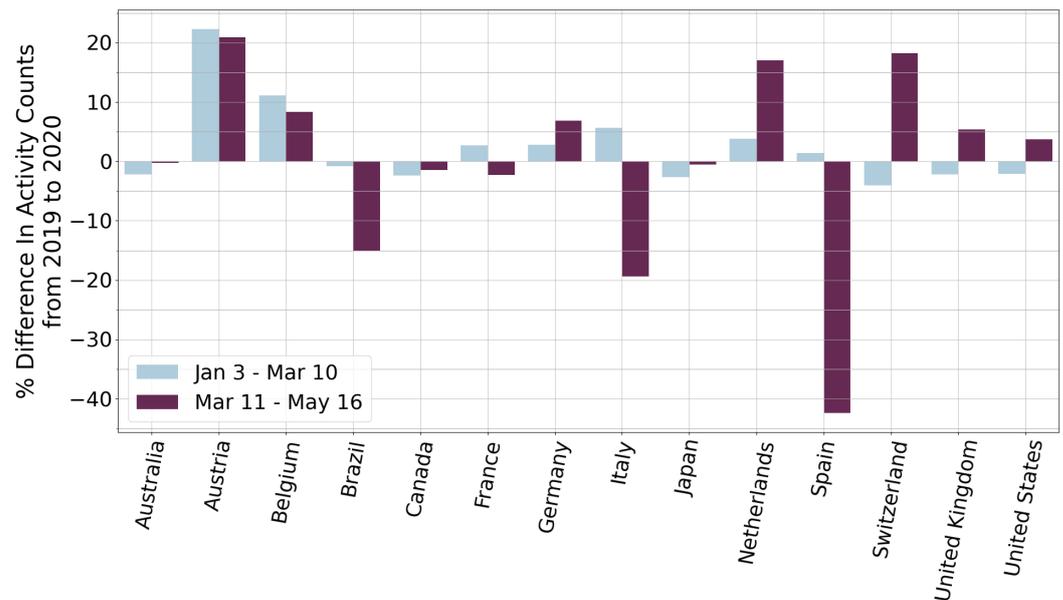


**Figure 1.** Distribution of user activity counts broken down by country and year.

##### Time-Series Activity Frequency by Country

Figure 3 display plots of activity counts and GRSI for the United States, United Kingdom, France, and Italy. Plots for all 14 countries that we analyzed are included in the supplementary materials (Figure S1). Figure 3 displays activity counts normalized by number of users for a given country, so activity levels can be directly compared between the pre-pandemic and the pandemic year and also between countries to identify which countries have residents who logged more or fewer activities than other countries' residents.

At the onset of the first lockdown periods beginning mid-March of 2020, the United Kingdom and United States' activity counts both decreased to below 2019 activity levels (Figure 3), immediately followed by an increase to activity levels which, for three months, were substantially higher than the corresponding 2019 activity counts. From September through the remainder of 2020, the slope of activity counts over time closely matched that of 2019, with activity counts trending down. Despite activity levels being higher in 2020 for



**Figure 2.** Percent difference in activity counts from 2019 to 2020 compared for the 67-day periods before and after the March 11 WHO pandemic declaration date.

three months following lockdown, they were generally substantially lower than 2019 levels for September through August for both countries.

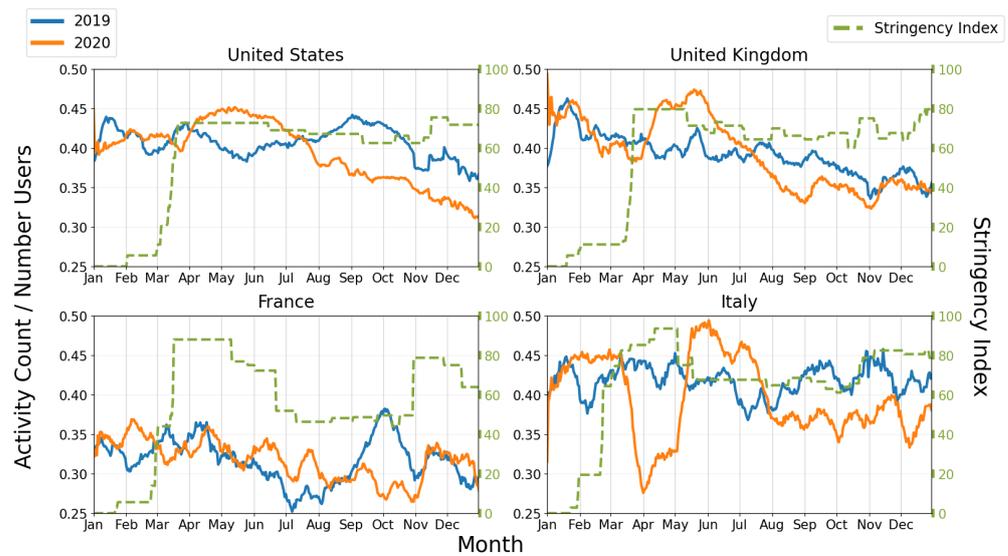
France instituted a severe lockdown from March 17 to May 11 and again from October 28 to December 15, where exercise was limited to within 1km of one's residence for less than one hour per day [28]. Interestingly, the activity levels of 2020 resemble that of 2019 for the period between March through June, suggesting that French users took advantage of their allotted 1-hour time to exercise during lockdowns, and lockdown did not have a large impact on the frequency of PA. In 2019, there was a large increase in activity counts in mid-September corresponding with a very popular race, La Parisienne, which occurred on September 9, 2019.

On March 9, a national lockdown was issued in Italy, and on March 22, all outdoor activities in public places such as parks and indoor facilities were banned. The GRSI indicates that restrictions in Italy were slightly more strict than in France. In late April, restrictions were eased and physical activity was allowed within 200 meters of one's residence [29]. We observe that activity rates in Italy were stable for the beginning of March, then dropped from about 0.45 to 0.28 activities per user per day (Figure 3), corresponding with the lockdown and increased GRSI. After Italy allowed greater freedom of movement as represented by decreased GRSI on May 4, rates rose from 0.33 to 0.49 activities per user per day, reaching above pre-lockdown levels. Italy's highest activity counts of 2020 occurred in May, right after lockdown was lifted.

Italy, France, and Spain reached the highest GRSI, respectively, among the 14 countries we examined (Figure S1). The highest GRSI for these countries occurred during the March-April lockdown periods, where GRSI fluctuated but remained close to 90 for each country. Figure 3 shows that during the March-April lockdowns, Italy's activity reached a minimum for the year at 0.28 activities/user daily, while France's activity levels remained mostly stable and closely matched 2019 activity levels with a minimum of 0.31 activities/user daily. Spain reached the lowest activity levels of all 14 countries in 2020 with 0.14 activities/user daily, despite having GRSI lower than France and Italy for most of March and April.

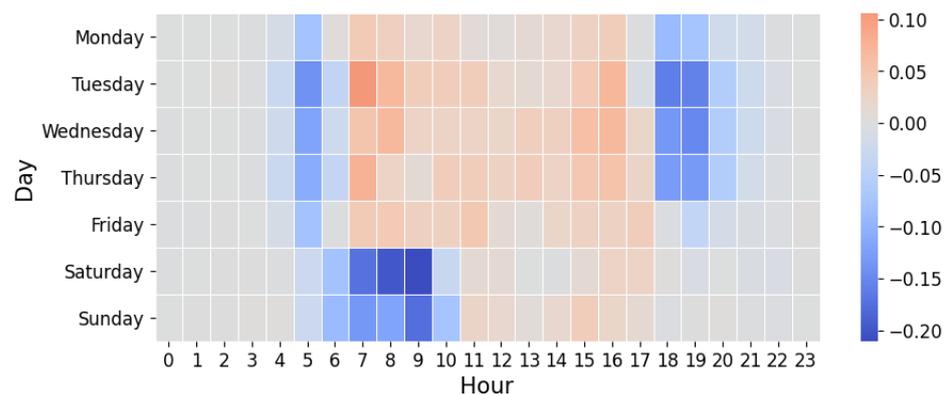
#### *COVID-19 and Timing of Exercise*

COVID-19 pandemic policies caused widespread workplace and school closures, cancellation of events, and travel restrictions.



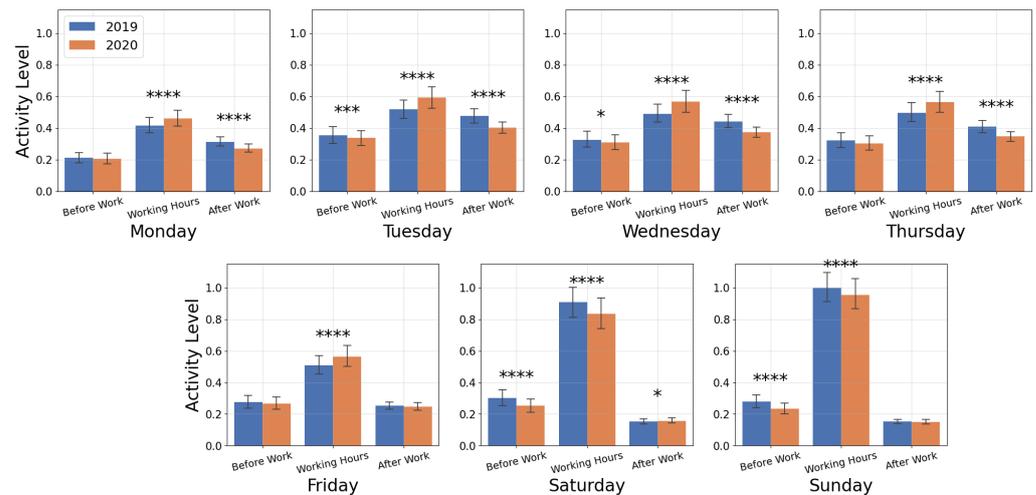
**Figure 3.** COVID-19 Government Response Stringency Index (GRSI) and daily activities counts per number of users in country using the controlled dataset.

We examined distribution of time when users began their recorded activities following the WHO pandemic date of March 11, 2020 throughout the end of the year and correspondingly the same period in 2019. The day-hour time bins with the greatest difference in activity counts between the two years are shown in Figure 4. The time bins with the greatest decrease are between 7-10 AM on Saturday and Sunday and between 6-8 PM (hours 18-20 in Figure 4) on Tuesday, Wednesday, and Thursday. Time bins with the greatest increase are 7-9 AM on Tuesday and Wednesday, 7-8 AM on Thursday, and 4-5 PM on Tuesday, Wednesday, and Thursday. Time bins with a reduction in activity counts mostly fall outside of traditional weekday working hours, while time bins with increased counts are the hours within working hours and especially hours tightly hugging the beginning and end of working hours.



**Figure 4.** Positive (red) and negative (blue) absolute change in normalized activity counts from 2019 to 2020.

Figure 5 shows that in the pandemic year, all five weekdays had significantly more runs logged during normal working hours ( $p < 0.001$ ), while weekends had significantly fewer runs during working hours, compared with the pre-pandemic year ( $p < 0.001$ ). Only Tuesday, Saturday, and Sunday showed a significant decrease in runs logged before working-hours for 2020 compared with 2019 ( $p < 0.001$ ). Monday, Tuesday, Wednesday, and Thursday also had significant decreases in activity counts after working hours for 2020 ( $p < 0.001$ ).



**Figure 5.** Normalized activity counts for the time periods before work (12 AM to 8 AM), during working hours (8 AM to 5 PM), and after work (5 PM to 12 AM). Significance with  $p < 0.05$  is denoted by \*, \*\* denotes  $p < 0.01$ , \*\*\* denotes  $p < 0.001$ , \*\*\*\* denotes  $p < 0.0001$ .

We also examined the time of activity for each of the 14 countries. See Supplementary File 1 for time-binned activity counts broken down by country and significance findings (Figure S2). The significant changes in time-binned activity shown in Figure 5 are generally reflected at the country level. Additional significant changes were detected for individual countries, for example Italy, Germany, and United Kingdom experienced increased activity before working hours on Monday ( $p < 0.05$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively). Other countries had significant changes that were opposite of the significant global trend identified in Figure 5. Notably, both France and Japan had a significant decrease in activities ( $p < 0.05$  and  $p < 0.01$ , respectively) logged during working hours on Monday, and Spain experienced a decrease during working hours on Tuesday and Wednesday ( $p < 0.01$  and  $p < 0.05$ , respectively) and a decrease after working hours on Saturday ( $p < 0.05$ ).

#### 4. Discussion

We used objective wearable device data for a retrospective analysis into physical activity behaviors prior to and during the COVID-19 pandemic. Currently, the body of research on PA during COVID-19 relies heavily on data collected via surveying people about their past PA habits and via objective device-tracking of step counts. Both can be very misleading, with survey data subject to recall bias and exaggeration, and step counts subject to user nonwear for dedicated athletic activities, such as playing soccer, climbing, or running where a user does not carry their mobile device [7,8,11,12]. Our analysis provides insight into a unique group of active individuals who purchased a footpod for the purpose of tracking more detailed information on their runs and overall running fitness. As such, we expect that running is a high priority activity for users, and they are also likely to be diligent about wearing the footpod for runs. Furthermore, as a retrospective analysis, we eliminate sources of behavior bias that can result when subjects are aware of their behavior being studied.

Overall, our analysis revealed variations across countries in PA behaviors. Countries enacted different pandemic policies, with Italy, France, and Spain respectively enacting the strictest lockdowns out of the 14 countries examined. Interestingly, Italy and Spain had the largest decreases in activity during lockdown periods while France had a relatively minimal decrease in activity counts. Previous work found that countries with higher government pandemic stringency were more likely to be insufficiently active [20]. France's PA is notable and should be investigated further because France reached the second highest stringency

index during their strict lockdown out of the countries we analyzed, but PA resembled the PA level of the pre-pandemic year.

Many countries experienced decreased PA during lockdown periods indicated by the spike in GRSI. Tison *et al.* examined smartphone step-counts during initial pandemic lockdowns and showed that Brazil, France, Italy, Japan, United Kingdom, and United States all experienced a decrease in steps comparing a pre-pandemic baseline on Feb 11, 2020 to every day in the period between April 1 and June 1, 2020 ranging from a 10% decrease to about a 47% decrease [14]. While step-counts were down, likely due to adherence to lockdown measures, shifting to remote work, and public closures, our work suggests that step-counts may not accurately reflect overall PA. Our work suggests that dedicated runners in Japan, United Kingdom, and United States increased logged PA from before to during the lockdown. Similarly, Venter *et al.* found an increase in recreational PA counts during initial lockdown using Strava data from 270,000 users logging runs, walks, hikes, and bike rides in Oslo, Norway [30]. More studies need to utilize logged activity data to assess its use and investigate the differences from step-counts and questionnaire data for measuring PA.

Previous work suggests that there was an increase in people working from home during the pandemic and increased sedentary behavior [7,31]. In our analysis of exercise timing throughout the week, we found that during 2020, users logged significantly more activities within standard working hours on Monday through Friday weekdays compared with 2019, and significantly fewer activities on weekends during the working hour period. Venter *et al.* similarly found that more running, hiking, and walking activities were logged during daylight hours, and fewer were logged in the mornings and evenings corresponding to this definitions of before work, working hours, and after work [30]. These effects may be due to the increased flexibility that came from pursuing work or education from home and the elimination of commuting. This may indicate that these times are preferred over times outside of working hours such as early morning or late evening, and it could also indicate that the reduced structure and increased flexibility of working at home may have contributed to decreased activity, or that people attempted to spread their exercise out over the day to avoid people and risk contracting the virus. Due to the large variation in pandemic workplace, school, public gathering, and other pandemic policy, COVID-19 case rates, health systems, and cultural and socioeconomic factors, it is not within the scope of this work to relate specific policies and cultural factors to observed PA behaviors within countries.

It is of widespread interest to determine whether working-from-home or hybrid work are workplace policies that would promote healthy PA. Future work could investigate those who exercised outside of working hours before the pandemic and shifted to exercising during working hours during the pandemic and whether they experienced increased or decreased PA. Furthermore, future analysis could investigate whether activity counts increased from the pre-pandemic year of 2019 to later years of the pandemic, to reduce the affect of the initial shock and panic of the pandemic. Previous questionnaire-based research indicated that habitually active individuals experienced a decrease in PA, while less active individuals were more likely to have increased PA [7,19,25,26]. We are interested in if this finding is supported by device-measured data, and if there is variation between countries.

This present study's strengths include that it examines global PA and also the individual PA of 14 countries using objective data for direct comparison across countries and before to during the pandemic. Also, the study uses a large sample size of over 7,000 subjects, reports analysis of logged physical activities instead of solely step-counts which most previous objective-tracking PA studies are limited by, and we cross-examine government pandemic response with PA levels. Limitations of this analysis are that it cannot explain the changes in PA. Possible factors for decreased activity counts in 2020 are that the pandemic was an extremely stressful time due to economic instability, isolation, disruption of regular life, fear of contracting the virus, and government pandemic policy. Another explanation for lower activity logging is that there were widespread in-person

race cancellations beginning in February, so users may have reduced their training due to race cancellations. The device strictly captures running activity of dedicated runners and misses other daily activity. Finally, our dataset may not have an accurate representation of socioeconomic groups who are less likely to own wearable devices.

## 5. Conclusions

This work aims to utilize wearables data, a data source unavailable during previous pandemics, for objectively-measuring physical activity in order to investigate the physical activity of runners during the COVID-19 pandemic. Activity counts generally decreased from 2019 to 2020, although eight of 14 countries examined had increased counts from the period before to the period after the date that the WHO declared a pandemic. We found that during the pandemic more activities were logged during normal working hours than before the pandemic, and the highest decrease in activities occurred in certain times outside of normal working hours. Studying the exercise trends during the COVID-19 pandemic will enable policymakers and public health officials to consider how to implement policies which encourage exercise to contribute to the overall health of the population. Further identification of factors leading to the increases in PA identified in this work could also guide public health officials in promoting healthy exercising.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/1010000/s1>, Figure S1: COVID-19 Government Response Stringency Index (GRSI) and daily activity counts per number of users for 14 countries in 2019 and 2020.; Table S1: title; Video S1: title.

**Author Contributions:** J.L.R. and Q.L. conceptualized the study. J.L.R. designed the methods, analyzed the data, and wrote the original manuscript. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Informed Consent Statement:** All subjects in the study consented to having data collected, stored, and shared by Stryd with third parties. The authors only received anonymized data and only reported aggregated information on subject groups.

**Data Availability Statement:** Restrictions apply to the availability of these data. Data was obtained from Stryd and are available from the authors with the permission of Stryd.

**Acknowledgments:** We would like to thank Dr. Kun Li and Stryd for sharing data with us and being supportive of this work.

**Conflicts of Interest:** J.L.R. was hired for temporary work by the company providing this dataset, Stryd. J.L.R. was hired after completing the analysis, while finishing the manuscript. Stryd had no role in the design of the study, the analyses or interpretation of data, the writing of the manuscript, or in the decision to publish the results. Stryd requested that the authors do not publish sensitive company information and approved the final manuscript.

## Abbreviations

The following abbreviations are used in this manuscript:

COVID-19	Coronavirus disease-2019
PA	physical activity
GRSI	Government Response Stringency Index
WHO	World Health Organization
AC	activity counts

## References

1. Bavel, J.; Baicker, K.; et. al, P.B. Using social and behavioural science to support COVID-19 pandemic response. *Nat Hum Behav* 2020, pp. 460–471. <https://doi.org/10.1038/s41562-020-0884-z>.

2. Tan, H.; Peng, S.; Zhu, C.; You, Z.; Miao, M.; Kuai, S. Long-term Effects of the COVID-19 Pandemic on Public Sentiments in Mainland China: Sentiment Analysis of Social Media Posts. *J Med Internet Res* **2021**, *23*. <https://doi.org/10.2196/29150>.
3. Sallis, J.F.; Adlakha, D.; Oyeyemi, A.; Salvo, D. An international physical activity and public health research agenda to inform coronavirus disease-2019 policies and practices. *J. Sport Health Sci* **2020**, pp. 328–334. <https://doi.org/10.1016/j.jshs.2020.05.005>.
4. Foley, L.; Panter, J.; Heinen, E.; Prins, R.; Ogilvie, D. Changes in active commuting and changes in physical activity in adults: a cohort study. *International Journal of Behavioral Nutrition and Physical Activity* **2015**, *12*, 1–12.
5. Sahlqvist, S.; Song, Y.; Ogilvie, D. Is active travel associated with greater physical activity? The contribution of commuting and non-commuting active travel to total physical activity in adults. *Preventive medicine* **2012**, *55*, 206–211.
6. Hicks, J.L.; Althoff, T.; Sosic, R. Best practices for analyzing large-scale health data from wearables and smartphone apps. *npj Digit. Med* **2019**, p. 2. <https://doi.org/10.1038/s41746-019-0121-1>.
7. Stockwell, S.; Trott, M.; Tully, M.; Shin, J.; Barnett, Y.; Butler, L.; McDermott, D.; Schuch, F.; Smith, L. Changes in physical activity and sedentary behaviours from before to during the COVID-19 pandemic lockdown: a systematic review. *BMJ open sport & exercise medicine* **2021**, *7*, e000960.
8. Park, A.H.; Zhong, S.; Yang, H.; Jeong, J.; Lee, C. Impact of COVID-19 on physical activity: A rapid review. *Journal of global health* **2022**, *12*.
9. Prince, S.A.; Adamo, K.B.; Hamel, M.E.; Hardt, J.; Gorber, S.C.; Tremblay, M. A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review. *Int J Behav Nutr Phys Act* **2008**, *5*. <https://doi.org/10.1186/1479-5868-5-56>.
10. Beagle, A.J.; Tison, G.H.; Aschbacher, K.; Olgin, J.E.; Marcus, G.M.; Pletcher, M.J. Comparison of the Physical Activity Measured by a Consumer Wearable Activity Tracker and That Measured by Self-Report: Cross-Sectional Analysis of the Health eHeart Study. *JMIR Mhealth Uhealth* **2020**, *8*, e22090. <https://doi.org/10.2196/22090>.
11. Shephard, R.J. Limits to the measurement of habitual physical activity by questionnaires. *British journal of sports medicine* **2003**, *37*, 197–206.
12. Dishman, R.K.; Washburn, R.A.; Schoeller, D.A. Measurement of physical activity. *Quest* **2001**, *53*, 295–309.
13. McCarthy, H.; Potts, H.W.W.; Fisher, A. Physical Activity Behavior Before, During, and After COVID-19 Restrictions: Longitudinal Smartphone-Tracking Study of Adults in the United Kingdom. *J Med Internet Res* **2021**, *23*, e23701. <https://doi.org/10.2196/23701>.
14. Tison, G.H.; Avram, R.; Kuhar, P.; Abreau, S.; Marcus, G.M.; Pletcher, M.J.; Olgin, J.E. Worldwide effect of COVID-19 on physical activity: a descriptive study. *Annals of internal medicine* **2020**, *173*, 767–770.
15. Ding, D.; del Pozo Cruz, B.; Green, M.A. Is the COVID-19 lockdown nudging people to be more active: a big data analysis. *Br J Sports Med* **2020**, pp. 1183–1187. <https://doi.org/10.1136/bjsports-2020-102575>.
16. The Effect of the Global Pandemic on Active Lifestyles. <https://www.garmin.com/en-US/blog/general/the-effect-of-the-global-pandemic-on-active-lifestyles>, 2020.
17. Activity Bounces Back as Lockdowns Lift, but Some Healthy Gains Are Slipping. <https://blog.fitbit.com/lockdowns-lift-mobility-changes>, 2020.
18. 2020 Year in Sport Data Report. <https://blog.strava.com/press/yis2020>, 2020.
19. Constandt, B.; Thibaut, E.; Bosscher, V.D.; Scheerder, J.; Ricour, M.; Willem, A. Exercising in Times of Lockdown: An Analysis of the Impact of COVID-19 on Levels and Patterns of Exercise among Adults in Belgium. *Int J Environ Res Public Health* **2020**, p. 4144. <https://doi.org/10.3390/ijerph17114144>.
20. Ding, K.; Yang, J.; Chin, M.K.; Sullivan, L.; Durstine, J.L.; Violant-Holz, V.; Demirhan, G.; Oliveira, N.R.; Popeska, B.; Kuan, G.; et al. Physical Activity among Adults Residing in 11 Countries during the COVID-19 Pandemic Lockdown. *International Journal of Environmental Research and Public Health* **2021**, *18*. <https://doi.org/10.3390/ijerph18137056>.
21. Bakel, B.; Bakker, E.; Vries, F.; Thijssen, D.; Eijvogels, T. Impact of COVID-19 lockdown on physical activity and sedentary behaviour in Dutch cardiovascular disease patients. *Netherlands Heart Journal* **2021**, *29*, 273–279. <https://doi.org/10.1007/s12471-021-01550-1>.
22. de Boer, D.R.; Hoekstra, F.; Huetink, K.I.M.; Hoekstra, T.; Krops, L.A.; Hettinga, F.J. Physical Activity, Sedentary Behavior and Well-Being of Adults with Physical Disabilities and/or Chronic Diseases during the First Wave of the COVID-19 Pandemic: A Rapid Review. *International Journal of Environmental Research and Public Health* **2021**, *18*. <https://doi.org/10.3390/ijerph18126342>.
23. Harrison, E.; Monroe-Lord, L.; Carson, A.D.; Jean-Baptiste, A.M.; Phoenix, J.; Jackson, P.; Harris, B.M.; Asongwed, E.; Richardson, M.L. COVID-19 pandemic-related changes in wellness behavior among older Americans. *BMC Public Health* **2021**, *21*, 755. <https://doi.org/10.1186/s12889-021-10825-6>.
24. Mutz, M.; Reimers, A.K. Leisure time sports and exercise activities during the COVID-19 pandemic: a survey of working parents. *Ger J Exerc Sport Res* **2021**, *51*, 384–389. <https://doi.org/10.1007/s12662-021-00730-w>.
25. da Silva Santos, A.M.; Rossi, F.; dos Santos Nunes de Moura, H.P.; de Sousa Junior, A.V.M.; Machado, D.C.D.; Neves, L.M.; Brito, A.S.; Moura, P.; Monteiro, P.A.; Júnior, I.F.F.; et al. COVID-19 pandemic impacts physical activity levels and sedentary time but not sleep quality in young badminton athletes. *Sport Sciences for Health* **2021**, pp. 1 – 9.
26. Brand, R.; Timme, S.; Nosrat, S. When Pandemic Hits: Exercise Frequency and Subjective Well-Being During COVID-19 Pandemic. *Frontiers in Psychology* **2020**, p. 347–365. <https://doi.org/10.3389/fpsyg.2020.570567>.
27. Hale, T.; Angrist, N.; et al, R.G. A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour* **2021**, p. 529–538. <https://doi.org/10.1038/s41562-021-01079-8>.

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28. Vila, J.; Capsec, J.; Bigoteau, M.; Pommier, K.; Cook, A.R.; Pisella, P.J.; Khanna, R. Impact of the first lockdown related to the COVID-19 pandemic on ophthalmic emergencies in a French University Hospital. *Journal Français d'Ophtalmologie* **2022**.
  29. Ravalli, S.; Musumeci, G. Coronavirus Outbreak in Italy: Physiological Benefits of Home-Based Exercise During Pandemic. *J. Funct. Morphol. Kinesiol.* **2020**, p. 31. <https://doi.org/10.3390/jfmk5020031>.
  30. Venter, Z.S.; Barton, D.N.; Gundersen, V.; Figari, H.; Nowell, M. Urban nature in a time of crisis: Recreational use of green space increases during the COVID-19 outbreak in Oslo, Norway. *Environmental research letters* **2020**, *15*, 104075.
  31. Koohsari, M.; Nakaya, T.; Shibata, A.; Ishii, K.; Oka, K. Working From Home After the COVID-19 Pandemic: Do Company Employees Sit More and Move Less? *Sustainability* **2021**.