**Comparing 24 h physical activity profiles: office workers, women with a history of gestational diabetes and people with chronic disease condition(s)**

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# Abstract

This study demonstrates use of a novel data-driven method of summarising accelerometer data to profile physical activity in three diverse groups, comparing results with cut-point determined moderate-to-vigorous physical activity (MVPA). Open-source software (GGIR) was used to generate average daily acceleration, intensity gradient (distribution), time in MVPA and MX metrics (acceleration above which the most active X minutes are accumulated) from wrist-worn accelerometer data from three datasets: office-workers (OW, N=697), women with a history of post-gestational diabetes (PGD, N=267) and adults with >1 chronic disease (CD, N=1,325). Average acceleration and MVPA were lower in CD, but not PGD, relative to OW (-5.2m*g* and -30.7min, respectively, P<0.001). Both PGD and CD had poorer intensity distributions than OW (P<0.001). Application of a cut-point to the M30 showed 7%, 17% and 28%, of OW, PGD and CD, respectively, accumulated 30 min of brisk walking per day. Radar plots showed OW had higher overall activity than CD. The relatively poor intensity distribution of PGD, despite similar overall activity to OW, was due to accumulation of more light and less higher intensity activity. These data-driven methods enable identification of aspects of activity that differ between diverse groups, which may be missed by cut-point methods alone.

**Key Words**: ACCELEROMETER, ACCELERATION, INTENSITY GRADIENT, MX METRICS.

**Abbreviations:**

Adults with >1 chronic disease - CD

Milli-gravitational unit - m*g*

Moderate-to-vigorous physical activity – MVPA

Office Workers – OW

Women with a history of post-gestational diabetes – PGD

Vigorous physical activity - VPA

# 1.0. Introduction

Physical activity plays an important role in health, for example higher levels of moderate to vigorous physical activity (MVPA) are associated with a lower risk of chronic disease and reduced all-cause mortality (Koolhaas et al., 2018; Saint-Maurice, Troiano, Berrigan, Kraus, & Matthews, 2018; Warburton, Nicol, & Bredin, 2006; Young and Haskell, 2018). More accurate assessment of physical activity through better quantification of the intensity and duration of activity undertaken could provide additional insight into associations with health outcomes (Wareham and Rennie, 1998). This could be achieved through device-based assessment of physical activity, e.g. body-worn accelerometers which can precisely measure movement over specified units of time, are not subject to participant recall bias, and are now in use in large studies globally (Troiano, McClain, Brychta, & Chen, 2014).

One of the most widely used activity outcome variables is time spent in MVPA. When accelerometers are used to assess activity, time spent in MVPA is usually established using an accelerometer wear-site specific, cut-point value; i.e. the accelerometer count or milli-gravitational unit (m*g*) value, above which the intensity of physical activity is classified as MVPA (Bassett Jr, Rowlands, & Trost, 2012). Presenting accelerometer data in this way is analytically straightforward and interpretable. However, it is difficult to compare activity outcomes across population groups, or even within populations, when MVPA cut-points are used as part of the analysis process. This is because the cut-points are population and protocol specific with many cut-points in regular use (Migueles, Cadenas-Sanchez, et al., 2019, Brazendale et al., 2016); consequently, study results differ depending on which MVPA cut points are applied to the data (Loprinzi et al., 2012).. The use of MVPA cut-points has recently been assessed by Migueles and colleagues, who stated it is ‘not possible (and probably will never be) to know the prevalence of meeting the physical activity guidelines based on accelerometer data’ (Migueles, Cadenas-Sanchez, et al., 2019). The limitations associated with the use of intensity cut-points, to summarise and analyse accelerometer data, identifies a clear need to revisit how accelerometer data are routinely expressed and the way in which accelerometer data are handled and analysed.

Since 2010, activity monitors that store high-resolution raw acceleration data rather than proprietary counts have been commercially available. Accompanying this, there has been a move from accelerometer wear on the hip to accelerometer wear on the wrist (Troiano, et al., 2014). Despite the richness of the raw acceleration data, and the problems outlined above, data are still frequently analysed using an intensity cut-point approach applied to the raw acceleration (m*g*) data. As a result, the limitations with the cut-point approach persist. This points to the need for a suitable alternative analysis method in order to facilitate comparison between studies. Furthermore, increasingly, the importance of focussing on the whole 24 h day has been stressed (Biddle et al., 2018; Tremblay et al., 2016).

Two accelerometer metrics that avoid cut-points and focus on profiling the 24 h day, using raw accelerometer data, are the average acceleration and the intensity gradient. The average acceleration is indicative of the volume of activity over a 24 h day, while the intensity gradient is a measure of the distribution of the intensity of activity; both metrics have been described previously (Rowlands, Fairclough, et al., 2019). In brief, a higher average acceleration indicates more activity over a 24 h period. The intensity gradient describes the negative curvilinear shape of the intensity spectrum (i.e., the higher the intensity the less time spent at this intensity). It is always negative, reflecting the drop-in time accumulated as intensity increases. A higher (less negative) intensity gradient indicates that the drop off in activity profile is less steep, reflecting a greater proportion of time accumulated at relatively higher intensities over the 24 h period. As these two metrics are more independent than traditional intensity metrics (e.g. time spent in MVPA) and average acceleration, used together they provide a complementary picture of the physical activity profile. To more meaningfully illustrate this 24 h profile, the intensity of the most active accumulated periods of the day can be presented as MX metrics (Rowlands, Sherar, et al., 2019). These are the minimum acceleration for the most active set time period (MX) where X denotes the time period of interest. By including a range of time periods from the very short (e.g. 2 min) to very long (e.g. ⅓ of the day or 8 h) it is possible to provide a novel and fairly comprehensive illustration of the activity profile (Rowlands, Dawkins, et al., 2019).

For example, the M30 describes the minimum acceleration value for the most active 30 minutes, with an M30 of 100 m*g* meaning that the most active 30 minutes of that person’s day was spent at an acceleration of 100 m*g* or above. This value can be compared to cut-points; e.g. an MVPA cut-point of 100 m*g* has previously been used to classify MVPA in adults (Hildebrand et al., 2014); therefore an M30 greater than 100 m*g* can be interpreted as achieving 30 min of MVPA per day. Notably the MX metrics can be compared to any intensity cut-point, unlike cut-point analyses where data are collapsed prior to analysis and cannot be subsequently compared to data analysed using a different cut-point (Rowlands, Sherar, et al., 2019). Furthermore, MX metrics will capture incidental activity as they focus on the most active minutes accumulated across the whole day.

Much of daily physical activity is incidental as has been described by Stamatakis and colleagues, i.e. physical activity which occurs as part of daily life (Stamatakis et al., 2019). An example of this may be anything from brief activities such as climbing the stairs, to longer periods such as completing housework (Jenkins, Nairn, Skelly, Little, & Gibala, 2019; Stamatakis et al., 2019). Non-structured or incidental physical activity is often hard to quantify or remember and as such is often missed when using self-report methods. Likewise, traditional accelerometer-based measures often use bout durations to determine sustained and purposeful activity so these too would not account for incidental physical activity.

These data-driven metrics are relatively new and subsequently their combined potential to describe activity profiles within and across populations has not been fully explored. As such, this study aims to use these metrics to demonstrate their use to comprehensively profile and compare physical activity, between three distinct groups: office workers, women with a history of gestational diabetes and people with one or more chronic disease, relative to traditional "cut-point" methods. For comparative purposes, the study will assess MVPA using a raw acceleration (m*g*) cut-point method.

# 2.0. Methods

## 2.1. Data source and study populations

The study used data from five studies, taken as a convenience sample of available data within the research unit, all of which assessed physical activity using wrist-worn accelerometers: office workers (OW); women with a previous diagnosis of gestational diabetes in pregnancy (PGD); adults with multi-morbidity, adults with type 2 diabetes, and adults 12 to 24 months post cardiac event diagnosis. All extracted measures were collected in line with the published protocols for each of the studies (Dallosso et al., 2018; Edwardson et al., 2018; Herring et al., 2018; Sukumar et al., 2018).

The SMART Work and Life (OW) data were obtained from adult office workers aged ≥18 years within local Councils in the Leicester, Manchester and Liverpool areas (N = 723). Details of the study have been published (Edwardson, et al., 2018).

Baby Steps (PGD) is a study involving women who had a previous diagnosis of gestational diabetes in pregnancy (N = 272). Participants were eligible to take part if they were up to 60 months post childbirth. Details of this study have been published (Sukumar, et al., 2018).

CODEC (Chronotype of Patients with Type 2 Diabetes and Effect on Glycaemic Control) is an ongoing study involving people with type 2 diabetes aiming to recruit ~2,000 participants. Data were obtained from adult participants aged 18-75 years (N = 712) currently enrolled in the study. Details of this study have been published (Brady et al., 2019).

MAP is a study involving people with two or more long term conditions aged 40-85 years recruited from primary care. Data were extracted for those with accelerometer data available at baseline (N = 346). Details of this study have been published (Dallosso, et al., 2018).

PACES is a study involving adults aged ≥18years, 12 to 48 months post diagnosis of a coronary heart disease related cardiac event. Data were extracted for those with accelerometer data available at baseline (N = 285). Details of this study have been published (Herring, et al., 2018).

The complete inclusion and exclusion criteria for each of the studies can be seen in the supplementary document (sections 2.1-2.5). All participants provided written informed consent. Where a study had multiple time-points, baseline data were used.

For the purpose of this study CODEC, MAP and PACES were combined into a chronic disease group (CD). All three groups contained people with similar characteristics as well as the conditions sharing common mechanisms. This newly merged group pooled data from participants with one or more chronic disease (N = 1,343). Information for each of these groups can be seen on the supplementary document (Table S1 and Figure S1).

## 2.2. Demographics

The following data were extracted from the relevant databases: age, sex, ethnicity, socioeconomic status (SES). In each study ethnicity was self-reported. Ethnicity was collapsed into categories of White European (WE), South Asian (SA), or Other, in view of the small number of people from other ethnic groups.

## 2.3. Anthropometric characteristics

Height and body mass and were extracted from each study dataset. BMI was calculated from this using the formula: Body mass (kg) / Height (m)2.

## 2.4. Physical Activity

In all samples, participants were requested to wear accelerometers on their non-dominant wrist 24 h a day for up to 8-days. In the PGD and CD groups the participants wore the GENEActiv (ActivInsights Ltd, Cambridgeshire, UK), while the OW group wore the Axivity AX3 (Axivity, Newcastle, UK). All monitors were initialised to record accelerations at 100 Hz. Available evidence suggests that physical activity outcomes from the GENEActiv and Axivity devices worn on the non-dominant wrist can be considered largely equivalent (Rowlands, Plehkanova, et al. 2019).

### 2.4.1. Accelerometer data preparation

All devices were initialised and downloaded using their specific software prior to receipt into this study. GENEActivs were initialised and data downloaded in binary format using GENEActiv PC (version 3.1). Axivity devices were initialised and data downloaded in .cwa format using OmGui open-source software (OmGui Version 1.0.0.30, Open Movement, Newcastle, UK).

All accelerometer files were processed and analysed identically with R-package GGIR version 1.9-0 (<http://cran.r-project.org>) (Migueles, Rowlands, et al., 2019). Signal processing in GGIR included auto-calibration using local gravity as a reference (Van Hees et al., 2014), detection of sustained abnormally high values, detection of non-wear, calculation of the average magnitude of dynamic acceleration (i.e. the vector magnitude of acceleration corrected for gravity (Euclidean Norm minus 1 *g*)) in milli-gravitational units averaged over 5 s epochs.

Following this process, participants were excluded if their accelerometer files showed: post-calibration error greater than 0.01 *g* (10 m*g*), fewer than three days of valid wear (defined as >16 h per day) (Rowlands et al. 2016), or wear data not present for each 15 min period of the 24 h cycle. Detection of non-wear has been described in detail previously (Van Hees, et al., 2014). The default non-wear setting was used, i.e. invalid data were imputed by the average at similar time-points on different days of the week; therefore, the outcome variables were based on the complete 24 h cycle (1440 minutes) for all participants.

The following outcomes were generated and averaged across all valid days (‘AD’ variables in GGIR): average acceleration (m*g*); total time in MVPA classified using a cut-point of 100 m*g* (Hildebrand et al., 2014) which has been widely applied in large studies (Barker et al., 2019a; Menai et al., 2017); intensity gradient; acceleration above which a person’s most active fraction of the day or X minutes (MX, m*g*) are accumulated: M⅓DAY, M120, M60, M30, M15, M10, M2 (GGIR qlevels: 960/1440, 1320/1440, 1380/1440, 1410/1440, 1425/1440, 1430/1440 and 1438/1440, respectively) (a full description of the accelerometer metrics used can be found in supplementary document Table S2). Average acceleration reflects the volume, or overall level, of physical activity. The intensity gradient reflects the distribution of the intensity of activity across the 24 h day and has been described elsewhere (Rowlands et al., 2018; Rowlands, 2018). In brief, it describes the negative curvilinear relationship between physical activity intensity and the time accumulated at that intensity during the 24 h day. The intensity gradient is always negative, reflecting the drop in time accumulated as intensity increases; a more negative (lower) gradient reflects a steeper drop with little time accumulated at mid-range and higher intensities, while a less negative (higher) gradient reflects a shallower drop with more time spread across the intensity range.

## 2.5. Analysis

### 2.5.1. Group comparison

Linear regression models were used to compare average acceleration, intensity gradient and MVPA between groups to identify if the PGD and CD groups were statistically different from the OW group which was designated the reference group. All models were adjusted for potential confounders (age, sex and ethnicity) and results were deemed significant at p<0.05. As the average acceleration and intensity gradient are not immediately interpretable, in order to visualise group differences in the physical activity profile, group means for the MX values were plotted on a radar plot as previously described (Rowlands, Dawkins, et al., 2019). This visualisation allows for interpretation of the activity profiles in relation to typical activities, e.g. slow walking and brisk walking. Connecting the data points for each group creates a shape reflecting the activity profile of each group. The further the shape is to the left of the radar plot (higher scores on the shorter time periods M2 to M15), the higher the intensity gradient. Dotted/ dashed circles show approximate values for slow walking (100 m*g*), brisk walking (250 m*g*) and vigorous physical activity (400 m*g*) taken from laboratory calibration studies (Hildebrand, et al., 2014). The brisk walking cut-point is taken from the regression equation presented by the authors for wrist acceleration and energy expenditure in adults. An acceleration of 250 m*g* predicted 4.3 METs, which according to the energy expenditure compendium (Ainsworth et al., 2011) is indicative of walking at a ‘brisk pace for exercise’, as previously described (Chudasama et al., 2019).These are used to translate the MX metrics, for example if the M30 is at the brisk walking dotted line this indicates 30 minutes of activity at an intensity equivalent to brisk walking or higher. To clearly illustrate relative differences between groups for each of the MX metrics a standardised plot is also presented. The MX metrics were standardised within metric relative to the mean and standard deviation (SD) of the reference group: the OW. The Z scores were plotted on the standardised radar plot, illustrating how each metric differs from the OW group in terms of SDs. These plots illustrate the intensity profile across which the volume of activity is accumulated. Linear regressions were run using Stata 16 (StataCorp LP, Texas, USA) and the radar plots were generated using a ggplot2 in R.

2.5.2. Illustration of physical activity profiles

The percentile distributions (5th, 10th, 25th, 50th, 75th, 90th, 95th percentile) of each MX metric were also graphed on radar plots for each group. Presenting percentiles for each metric clearly illustrates the magnitude of the most active X minutes, from the least to the most active participants, within each sample. Translating this information using a cut-point in retrospect allows identification of the proportion of each sample meeting the MVPA guidelines. All known values or cut points were added to the figures post-hoc in a ‘translation phase’ and have no bearing on the generation of the metric values themselves.

# 3.0. Results

Descriptive statistics for each of the datasets included in this secondary analysis are presented in Table 1. Accelerometer data files were available for 2,339 participants: 723 OW, 272 PGD and 1,344 CD participants. Data were invalid for 26 from the OW group (failed calibration N = 5, insufficient wear N = 21). Five participants were excluded from the PGD group (insufficient wear N = 5) and 19 participants from the CD group (initialisation error N = 6, failed calibration N = 1, insufficient wear N = 12). Thus, a total of 2,289 participants were included in the analysis: 697 OW, 267 PGD and 1,325 CD.

## 3.1. Intensity and Volume of the 24 h physical activity profile

The measures for volume (average acceleration) and intensity distribution (intensity gradient) of physical activity are presented in Table 1. Average acceleration of the OW group was significantly higher than the CD group, but not the PGD group. Both the CD and the PGD group had a significantly lower (worse) intensity gradient than the OW population. The values for time spent in MVPA showed the same pattern as the average acceleration, with the OW group, accumulating significantly more time in MVPA than CD group, but not the PGD group.

## 3.2. MX Values

The MX metrics are plotted below on Figure 1 a (raw values) and b (standardised plot). As expected from the average accelerate on and intensity gradient values, the radar plots also indicate the CD group had the lowest acceleration on each MX metric. All three groups achieved around 60 minutes of slow walking (Figure 1a). The OW group achieved approximately 15 minutes of brisk walking, whereas the PGD group managed 10 minutes and the CD group only 2 minutes. The OW and PGD groups achieved 2 minutes of vigorous physical activity (VPA), however the CD group on average did not achieve any VPA.

When examining the standardised plot (Figure 1b), the PGD group had relatively high values for the M120 and M⅓DAY metrics, indicative of large volumes of lighter intensity activity. In contrast the OW group showed the highest values for the shorter duration, relatively high intensity MX metrics.

## 3.3. Percentile distribution of MX metrics

Presenting the data in percentile radar plots allows identification of the proportion of each group achieving a known value, such as a cut-point or guideline (Figure 2, a-c). Using these values, for example, the proportion of the participants that achieved 15 minutes of brisk walking can be identified. The OW group had the highest proportion achieving this at 33% (Figure 2a). The PGD group had around 13% less achieving this at 20% (Figure 2b) and only 7% of the CD group achieved 15 minutes of brisk walking (Figure 2c). Similarly, in the OW group, 44% achieved 2 minutes of VPA for the PGD group this was slightly less at 38%, whereas only 15% of the CD achieved 2 minutes of VPA.

# 4.0. Discussion

This study provides novel insight into complex physical activity profile data across three distinct groups: office workers, females with a previous gestational diabetes diagnosis and individuals with one or more chronic disease, relative to traditional "cut-point" methods.The CD group had the poorest physical activity profile overall. This was evidenced by lower values for both volume and intensity distribution of activity, which were reinforced when visualised using radar plots displaying different MX metrics. This is consistent with the literature which shows that people who suffer with a chronic condition are generally less active (Koolhaas, et al., 2018; Saint-Maurice, et al., 2018; Warburton, et al., 2006; Young and Haskell, 2018). Expressing physical activity simply as time spent in MVPA would have also shown this. However, when examining the PGD group, physical activity expressed as time in MVPA or overall volume was not significantly different to that of the OW group. Nevertheless, these two groups did differ in terms of the intensity distribution of their physical activity, with less time spent in higher intensities of physical activity compared to the OW group, demonstrating two very different physical activity profiles for the same overall physical activity volume. The radar plots allow the identification and visualisation of where in the physical activity profile these differences occurred. For example, the greater intensity of the activity of the OW group across the shorter (<60 min), but not longer (>120 min), duration MX values explains the differing intensity distribution profiles denoted by the significantly higher intensity gradient. The relatively high values for M120 and M⅓DAY in the PGD group suggests a lot of time spent ‘pottering around’, likely in incidental habitual physical activity.

Establishing the proportion of each group achieving a guideline or recommendation beneficial for health can provide further insight. This is particularly relevant with regards to translation of research as putting the information in a way that is understandable is key to conveying the information either individually or at population level. The assessment of meeting guidelines using the MX metrics follows a similar concept to the use of cut-points to establish time spent in MVPA (Migueles, Cadenas-Sanchez, et al., 2019, Rowlands, Dawkins, et al., 2019A. V. Rowlands, N. P. Dawkins, et al., 2019)) but applies the cut-points post-hoc. This maintains the continuous nature of the accelerometer metrics rather than collapsing the data, thus allowing use of any cut-points for interpretation. Despite the mean time spent in MVPA being slightly higher (non-significant) in the PGD group than the OW group, the PGD group had relatively high variability and the OW group had over 10 percent more of the sample achieving at least 15 minutes of brisk walking. This is pertinent as it has recently been shown that walking briskly for more than 10 minutes a day is associated with a longer life expectancy (Chudasama, et al., 2019). There was a clear difference between the PGD and CD groups with more than double the proportion of the PGD sample accumulating 15 min of brisk walking. However, the groups had a mean difference in age of approximately 30 years, therefore age could have played a role in this as physical activity declines with age (Bohannon, 1997; Bohannon and Williams Andrews, 2011).

At present, activity guidelines are generated largely based on evidence from self-report data. However, ultimately the ideal scenario would be that accelerometer-based guidelines are generated (Troiano, et al., 2014) as this would facilitate appropriate interpretation of accelerometer measured physical activity. In the current study we have translated results in terms of known acceleration values for given activities (Hildebrand, et al., 2014), e.g. 250 m*g* as an acceleration cut-point indicative of brisk walking. It should be noted that these cut-point values were generated from data on a fairly small sample of healthy individuals and therefore may not be appropriate for all populations. For example, it has previously been suggested that a lower cut-point should be used for a population with chronic disease (Dibben, Taylor, Dalal, & Hillsdon, 2019), but currently this is not possible as cut-points are not widely available for all population types (Barker et al., 2019b). We chose to translate our data in terms of brisk walking as it is easily interpretable and has strong evidence for beneficial health outcomes (Yates et al., 2017). Translation of accelerometer data will develop as the bank of raw accelerometer data available for specific populations is built. If population-specific values were established for brisk walking, for example by age, these estimates could be used with more confidence for public health messages. This would be beneficial from a translational perspective as brisk walking lends itself to activity recommendations as it is easy to interpret and could be tailored to specific populations.

There are some limitations in the current study. Firstly, although sample sizes within each group were large, the sample size varied across groups which might impact on the generalisability of the findings. A different accelerometer device was used for the OW group, however physical activity outcomes from the two monitors deployed have been reported to be largely equivalent (Rowlands, Plekhanova, et al., 2019). All the devices were wrist worn, reflecting the general move to deployment of wrist-worn accelerometers. While wrist-worn devices have been shown to be valid (White et al., 2019; White, Westgate, Wareham, & Brage, 2016) and are useful for capturing overall data it should be noted that data are not directly comparable with data from hip-worn devices. The values for MVPA were relatively high, but consistent with studies using similar protocols. This has previously been attributed to capture of all incidental movements not merely structured ones (Barker, et al., 2019a). Further, seven days of activity data were used to represent habitual activity. Whilst this is widely accepted (Dillon et al., 2016), it does not capture seasonal variation.

The main strength of this study is utilisation of accelerometer measures of physical activity and data-driven methods to quantify the 24 h profile of physical activity in different populations. This allowed the full intensity distribution of physical activity to be considered. It also highlights how the use of a relatively novel method for analysis and translation of accelerometer data can facilitate insights into how the activity profiles differed across three distinct groups. Using these data-driven metrics captured more information than MVPA, which focuses on a very small proportion of the 24 h day, allowing a more comprehensive comparison of physical activity profiles between groups. In addition, use of the GGIR open software to process the data meant that all devices were processed in the same way reducing the difficulties previously seen with comparing different devices.

This has implications for future research; identification of the relative importance of intensity and volume of physical activity for a given health marker and translation in terms of the MX metrics (all of which can be generated using the open source package, GGIR) may facilitate choice in activity recommendations. For example, we recently showed that while adiposity was optimum when activity volume and intensity were high, some benefit was also achieved were achieved with either high volumes of low intensity activity or smaller volumes of higher intensity physical activity (Rowlands, Fairclough, et al., 2019). Future research should assess how the physical activity profile is related with health outcomes by age and disease categories with a view to informing accelerometer-driven physical activity prescriptions and recommendations. Choice in physical activity recommendations may lead to greater autonomy and ultimately greater adherence. This could be beneficial for precision medicine and an individualised approach for prescribing physical activity.

# 5.0. Conclusion

In conclusion, using data-driven accelerometer analysis and translation metrics to profile physical activity provides an effective way of comparing and describing different groups. The outcomes of this study show that using 24 h accelerometer metrics provides key information about physical activity profiles that may be missed when relying on methods which collapse data upfront, particularly when there is no consensus on the method of collapsing data, e.g. intensity cut-points, as these are known to be population and protocol specific.

**Acknowledgements:** The authors thank all researchers, project staff and participants involved in the SMART Work and Life trial, BABYSTEPS (females with a previous diagnosis of gestational diabetes in pregnancy), CODEC (adults with type 2 diabetes), MAP (adults with multiple comorbidities) and PACES (adults 12 to 48 months post a coronary heart disease cardiac event diagnosis) trials for access to the data used herein. University of Leicester authors are supported by the NIHR Leicester Biomedical Research Centre, and the NIHR Applied Research Collaboration (ARC) East Midlands. The views expressed are those of the authors and not necessarily those of the NHS, NIHR, or Department of Health.

**Author Contributions:**  NPD, AVR and TY planned the study. NPD completed the main analysis of the study, with contributions from AVR and BM. NPD prepared the first draft of the manuscript. All authors read, provided feedback and approved the final manuscript.

**Disclosure of interest:**  The authors report no conflict of interest.

**Funding:** No funding was received to conduct this research.

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# 7.0. Tables

**Table 1**. Descriptive characteristics and physical activity for each group. Values are presented as mean (standard deviation) or N [%].

|  |  |  |  |
| --- | --- | --- | --- |
|  | Office workers (N = 697) | Post gestational diabetes (N = 267) | Chronic disease (N = 1,325) |
| Age (y) | 44.7 (10.4) | 35.3 (4.9) | 65.2 (9.1) |
| Height (cm) | 166.5 (8.9) | 162.8 (7.1) | 168.9 (9.4) |
| Mass (kg) | 73.3 (17.7) | 77.5 (18.5) | 86.9 (17.6) |
| BMI (kg/m2) | 26.4 (5.9) | 29.1 (6.1) | 30.3 (5.2) |
| Ethnicity (White European) | 522 [75] | 267 [100] | 1,174 [90.7] |
| Sex (Female) | 506 [72.7] | 267 [100] | 435 [33.3] |
|  |  |  |  |
| Average Acceleration (m*g*) | 27.4 (7.3) | 29.3 (6.9) | 22.2 (7.0)\* |
| p value | - | 0.286 | <0.001 |
| Intensity Gradient | -2.55 (0.21) | -2.62 (0.16)\* | -2.74 (0.21)\* |
| p value | - | < 0.001 | <0.001 |
| Total MVPA per day\*\* (min) | 99.1 (35.6) | 108.4 (44.4) | 68.6 (40.8)\* |
| p value | - | 0.843 | <0.001 |
| Significantly different from the office workers group (p<0.01) = \* (Covariates: ethnicity, sex, age)  MVPA = moderate-to-vigorous physical activity  \*\* MVPA calculated using a 100m*g* cut-point (Hildebrand, et al., 2014) | | | |

# 8.0. Figures

**Figure 1.**

**A picture containing text, map

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**Figure 2.**

A close up of a map

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# 9.0. Figure List

**Figure 1.** MX values: M⅓DAY, M120, M60, M30, M15, M10, M5 and M2, for all three study groups.The red dashed lines representing indicative values for: slow walking (---), brisk walking (…) and vigorous activity (.\_.\_.)(Hildebrand, et al., 2014). OW = Office Workers, PGD = women with a history of post-gestational diabetes, CD = adults with >1 chronic disease.

1. Mean MX values (m*g*); **b)** Standardised MX values.

**Figure 2.** Percentile distribution of MX metrics for each of the three groups. The red dashed lines representing indicative values for brisk walking (…) and vigorous activity (.\_.\_.) (Hildebrand, et al., 2014).

1. Office workers (OW); **b)** Women with a history of post-gestational diabetes (PGD); **c)** Adults with >1 chronic disease (CD).