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Socio-demographic determinants of physical activity and app usage from smartphone data

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ABSTRACT

The increasing ubiquity of smartphones provides a potential new data source to capture physical activity behaviours. Though not designed as a research tool, these secondary data have the potential to capture a large population over a more extensive spatial area and with longer temporality than current methods afford. This paper uses one such secondary data source from a commercial app designed to incentivise activity. We explore the new insights these data provide, alongside the sociodemographic profile of those using physical activity apps, to gain insight into both physical activity behaviour and determinants of app usage in order to evaluate the suitability of the app in providing insights into the physical activity of the population. We find app usage to be higher in females, those aged 25–50, and users more likely to live in areas where a higher proportion of the population are of a lower socioeconomic status. We ascertain longer-term patterns of app usage with increasing age and more male users reaching physical activity guideline recommendations despite longer daily activity duration recorded by female users. Additionally, we identify key weekly and seasonal trends in physical activity. This is one of the first studies to utilise a large volume of secondary physical activity app data to co-investigate usage alongside activity behaviour captured.

1. Introduction

Physical inactivity is the fourth leading global risk factor for non-communicable disease in the world (World Health Organization et al., 2010), responsible for an estimated one in six deaths in the UK (Public Health England, 2019). Subsequently, there is a large body of research and policy guidance aimed at increasing the physical activity levels of different populations (Kahn et al., 2002). The first step to increasing physical activity levels of a population is understanding the current levels of, and barriers to, physical activity.

Capturing physical activity is difficult, with traditional methods such as interviews and surveys relying on participant recall. These self-reported methods have issues relating to memory and social desirability bias (Sylvia et al., 2014), often leading to an overestimation of physical activity (Janevic et al., 2012). Nonetheless, these self-report methods are advantageous in their ability to survey a representative sample. Questionnaires which aim to capture physical activity, for example via measurements of active transportation, are often temporally limited. Questions typically only capture recent activity (in the last week or month) and hence limit the ability to represent habitual activity patterns (Shephard, 2003). Moreover, methods of capturing physical activity historically tend to measure only traditional forms of physical activity (Sylvia et al., 2014), such as running, cycling and walking. Yet, the World Health Organization (2018) define physical activity as “any form of bodily movement performed by skeletal muscles that result in an increase in energy expenditure”. Physical activity therefore incorporates a wide range of activities, from traditional sports and walking, to any activity that requires increased energy expenditure, such as gardening and cleaning.

In recent years, pedometers and accelerometers have played a more prominent role in physical activity studies, producing quantifiable measures of all physical activity and removing risk of recall bias and gaps in memory due to constant recording (Skender et al., 2016). However, such studies are typically expensive to conduct on a large scale. Cost, coupled with the burden of wearing and charging a new device, means studies are often short in duration, rarely exceeding 7

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days (McCormack and Shiell, 2011). They also typically have smaller sample sizes than surveys. Therefore, the temporal coverage of the activity recorded arguably does not capture habitual activity. Recruitment bias is also an issue in both self-reported and objectively recorded physical activity studies: it has been observed that participation uptake is higher in those with specific socio-demographic characteristics such as higher income and level of education (Waters et al., 2011).

Advances in technology are resulting in individuals increasingly choosing to track their own activity. Smartphones contain built in accelerometers and GPS tracking recording metrics such as step count and distance moved. Furthermore, wearable devices such as Garmin, Fitbit or Apple watches (or similar waist worn activity trackers) record analogous metrics which, depending on model, offer additional capacity to record heart rate, sleep patterns and to distinguish activity types. This increase in physical activity tracking has led to an estimated 14.2 million fitness app users and 6.3 million wearable activity tracker users in the UK in 2018 (Blumtritt, 2018). Smart phone and wearable data are available to the user via a health app interface, which allows them to view numerous metrics quantifying their activity behaviour, track trends in daily activity and even compare their performance to and compete with friends, family or strangers.

Data from physical activity apps provide granular information on activity behaviour of an individual over an extended time period. Such datasets do not face the same sample size and temporal coverage limitations as previous methodologies. These data are also advantageous in their automatic linking of activity with place through the use of smartphone GPS. However, whilst the potential new insights to be gained from these secondary data are considerable, they also present challenges. Smaller scale primary studies using commercially available apps and wearable trackers have looked to validate such data for different population groups and settings (Evenson et al., 2015; Hekler et al., 2015). Nonetheless, the scale of these secondary data present additional difficulties. Hicks et al. (2019) identify some of the main challenges, including measurement and selection bias and the issue of missing and messy data, which may arise from non-continual app usage, resulting in gaps in activity recording (Lin et al., 2018). Equally, the app may fail to capture all activity: an individual using their phone to record activity may not use it to record contact sport activity or swimming. In terms of selection bias, it is postulated that the unique selling points of different apps will appeal to different populations. Both Strava and Argus app users were more likely to be male and younger compared to the population as a whole (Griffin and Jiao, 2015; Althoff et al., 2017). Subsequently, app user populations captured may not be demographically representative of the general population. This is similar to the issues of generalisability due to recruitment bias present in survey and interview data (Cooke and Jones, 2017). Another key consideration is the role the app plays in motivating and incentivising physical activity and therefore, implications of the physical activity data recorded. These motivators range from the act of using the app itself, which has been found to increase activity (Litman et al., 2015), the social or challenge-based elements of the app as seen in Strava (Griffin and Jiao, 2015), gamification (Shameli et al., 2017) and reward (Mitchell et al., 2018).

In this paper we utilise data from an app which to date has not been widely used for research. The Bounts app, launched in 2011, was designed to incentivise physical activity by rewarding users for higher activity levels. The dataset comprises of physical activities recorded by over 30,000 users for a 12-month period. It also includes the user's basic demographic information. The primary aim of this paper is to utilise these secondary data to capture habitual activity behaviour and to use the demographic and spatial information to characterise the Bounts app-user. We evaluate the extent to which app users are representative of the general UK population. To address the challenges of using secondary app data (Hicks et al., 2019), we characterise both app usage and physical activity behaviour. We additionally identify the limitations of this secondary health app data source and evaluate its suitability and utility for undertaking physical activity research.

2. Methods

Following 'best practise by guidance' established by Hicks et al. (2019), an iterative process was used to characterise the data, identify appropriate research questions, define data cleaning thresholds and define the population of interest. Following this process, we identify the demographic and socioeconomic characteristics of the user population from active app user profiles. We then characterise both patterns in usage of the Bounts application and patterns in physical activity behaviour, including likelihood to meet physical activity guidelines, by examining how these usage and physical activity behaviours vary by the socio-demographic characteristics of users.

2.1. App source and data overview

This study utilises smartphone app data provided by Fuell Limited from their commercial app "Bounts", which can be accessed by application to the UK Consumer Data Research Centre (Consumer Data Research Centre, 2017). The Bounts app is available to download from the app stores of all major UK phone operating systems (Android and iOS) and uses activity data from a broad range of activity tracking apps and wearable devices. To use the app, individuals have accepted terms and conditions indicating that they acknowledge their data may be used for research purposes. The user can see a dashboard summary of their activity as well as receive a points tally to incentivise activity. Points could be won for completing certain amounts of activity and completing challenges. These points could then be accumulated and exchanged for prizes such as gift vouchers, prize draw entries or merchandise through the app. We utilise Bounts app data of users from January 01, 2016–December 31, 2016. On signing up for the app, the user had the option to enter their year of birth, gender and postcode, which are assigned to their own unique pseudonymised ID. Only the first four characters of the postcode were provided by Fuell Limited in order to prevent identification of individuals. Thus, the smallest possible area identifiable is the postcode sector, an area with a population of around 5000 individuals.

Activity data were recorded as a daily summary for each activity type, on each day the user recorded activity. Activity types include, but are not limited to, 'move', walking, running, cycling, and swimming. 'Move' activities encompassed more general walking and everyday movement gradually accumulated throughout the day. For each type of activity, the following metrics, where relevant, were recorded: activity speed, duration and number of steps taken while completing the activity. Subsequently, we can also extrapolate total daily activity metrics for the users such as daily step count and total distance moved. Independent activity data and daily summary data were linked to the user demographic profile via the unique pseudonymised ID. The supplementary materials provide a full overview of the data available following the BEE-COAST framework for reporting big data sources in obesity research (Morris et al., 2018).

We use the following terminology to distinguish between a user having the app, using of the app and physical activity recoded by the app. User and usership refers to the unique individuals using the app. Usage refers to each time the app is used to record activity. Physical activity behaviours are captured by the aforementioned metrics such as step count, activity duration etc.

2.2. Data cleaning and pre-processing

With no standard methodology for cleaning secondary activity data, a replicable data cleaning approach was devised. Following iterative data exploration and visualisation, any impossible or improbable activities were removed in order to capture usual or habitual activity of the users. The full data cleaning process is outlined in the supplementary materials and the full python code is available as a GitHub repository (Pontin, 2020). Duplicated activity data was removed; for example, when the same metrics were recorded by a single user on the same day but by different trackers. Activities lasting longer than 24 h were also removed due to low likelihood of occurrence and to prevent duplication of activity captured. Activities were then cleaned based on the 99th percentile for speed and distance. Activities in the top 1 percentile were deemed improbable and not reflective of habitual activity (e.g. cycling activities with an average speed of over 39.1 km/h).

Alongside the activity data, user data were also cleaned. Users with less than 7 days of recorded activity were removed from the sample to capture habitual activity patterns (Bergman, 2018) and longer-term app usage. Moreover, only individuals who provided both their age and gender were included in the final analysis. The pseudonymised ID was then used to link the demographic information with the daily activity summaries for each day recorded activity during the 2016 period. Annual average metrics for each user were calculated, including their annual mean activity duration, speed and step count across all activity types. The total number of different types of activity conducted by each user in the year, including their most popular activity and the number of different tracking methods used, were additionally calculated.

To conduct socioeconomic analysis, postcode data was cleaned to postcode district level and linked to the National Statistics Socio-economic Classification (NS-SEC), an occupational classification for the entire adult population of England and Wales from census data (Office for National Statistics, 2012). Consequently, socioeconomic analysis was only conducted for users living in England or Wales. Class labels are provided in Table 1 and are described in detail elsewhere (Office for National Statistics, 2012).

2.3. Data analytics

2.3.1. Demographic variation in app usage

Demographic variations in usage behaviours are valuable for classifying participant behaviours. Summary statistics were calculated to capture the number of days of activities recorded by each user and average number of days activity recorded by age. As we are utilising secondary app data, there was no study participation incentive for users to record activity every day and the first date of usage was staggered. Hence, the number of days of activity recorded above the 7-day cut-off varied widely from user to user. A Mann-Whitney *U* test was undertaken to compare the median number of days of activity for male and female users. Spearman rank correlation was then used to determine the level of association between age and average number of days of recorded activity disaggregated by gender.

Table 1
Comparison of the NS-SEC distribution of postal districts in which Bounts users live compared to the NS-SEC distribution for the population of England and Wales.

NS-SEC class	(Mean) distribution of population by NS-SEC (%)		Mann Whitney *U* test for difference (p)
	For bounts users	For population of England & Wales	
1. Higher managerial, administrative & professional occupations	10.24	10.75	<0.01
2. Lower managerial, administrative & professional occupations	21.11	21.48	<0.01
3. Intermediate occupations	13.28	12.44	<0.01
4. Small employers and own account workers	9.34	10.71	<0.01
5. Lower supervisory and technical occupation	7.22	6.95	<0.01
6. Semi-routine occupations	14.46	13.79	<0.01
7. Routine occupations	11.43	10.60	<0.01
8. Never worked and long-term unemployed	4.96	4.93	<0.01
Not classified	7.95	8.35	<0.02
Total	**100.00**	**100.00**	

2.3.2. Socio-economic variation in app usership

The distribution of users in postcode districts where the proportion of NS-SEC is known were compared to the distribution of population socioeconomic status in all postcode districts in England and Wales. Socioeconomic classification of the postal districts in which users live was explored to characterise the usership in comparison to the general population. However, we can only infer the socioeconomic differences between the districts in which individuals live and not the socioeconomic status of the users themselves. A Mann-Whitney u test was used to compare the proportion of different NS-SEC classes in postal districts in which users lived to the average proportions for England and Wales.

To identify whether the postcode user group has a measurably different demographic compared to the group for which we have no valid postcode data, the two subsets of the Bounts population were compared. Population size of areas where users lived were compared using a *t*-test to areas where no Bounts users had a linkable postcode. The proportion of male and female users with and without a valid postcode were also compared using a chi-squared test.

2.3.3. Temporal variation in activity volume

Temporal variations in the volume of activity recorded by the app were explored to identify if any significant annual or short-term trends existed in activity patterns. Count of daily activities recorded by all users on each day of the year was used as a proxy for activity volume, capturing both app usage on that day and physical activity occurrence. Heat maps were used to visualise daily variations in activity volume across the year. To investigate weekly trends, seasonal trends were standardised. The average number of activities per user was calculated for each week and the mean calculated to obtain average activity count across all users for each week of the year. For each day of the week, the absolute deviation of the average activity count across all users for that day from the weekly average was determined. This effectively controls for seasonal patterns.

2.3.4. Demographic and socioeconomic variations in physical activity

It is postulated that preference for type of exercise will vary by age and gender. To compare activity type popularity by age and gender, the proportion of activities of each type were calculated and compared across demographic characteristics. To further understand potential demographic variations in more general activity behaviours, aggregate activity behaviours were also explored. For each user's average daily step count, average daily duration of activities both including and excluding 'move' activities were calculated. Activity variety was explored by determining the total number of different activities recorded over the year by each user and the average number of different activities recorded daily by the user. Socioeconomic, age and gender variations in these general activity behaviours were then explored. To investigate socioeconomic status, users living in areas where the highest proportion (5th quintile) of the population hold professional and managerial roles (NS-SEC class 1) were compared to areas with the lowest proportion of NS-SEC class 1 (1st quintile).

From the daily activity summary metrics it was possible to explore the demographic determinants of meeting physical activity guidelines of $\geq$150 min of moderate to vigorous activity (World Health Organization et al., 2010). 'Active minutes' were calculated as the duration of the activities undertaken by an individual, summed for each calendar week. 'Move' activities, with an average speed of $\geq$5 km/h to capture brisk walking and all other activity types, were presumed to meet the definition of moderate activity (Department of Health and Social Care, 2019) and therefore were included in the active minutes calculation. Activities classified as 'Move' slower than 5 km/h were more likely to be accumulated throughout the day in short bursts or at low intensity and therefore not meet the moderate intensity guideline criterion. For each individual, the percentage of weeks they recorded ≥150 active minutes was also calculated. Demographic determinants of meeting physical activity were explored by calculating the average percentage of weeks the guidelines were met, disaggregated by age and gender, and the distributions were visualised. The percentage of weeks users met physical activity guideline in areas with the highest proportion and lowest proportion of the population classed as NS-SEC class 1 were compared using a *t*-test.

3. Results

Following activity cleaning and inclusion of users with at least 7 days of recorded activity (n = 32,948), 8,585,648 activities were undertaken by Bounts users with known age and gender in 2016 (n = 30,804, 93.5 %). Of the remaining users with 7 days' recorded activity, 1190 (3.6 %) users entered neither age or gender data, 720 (2.2 %) entered only gender demographic information and 234 (0.7 %) entered only age information. Analysis of the determinants of app usage and physical activity behaviour were conducted for these 30,804 app users with both known demographics and valid habitual activity data. 22.3 % (n = 6871) of users were male and 77.7 % (n = 23,933) female, and users had an average age of 39 (SD = 10.00). Users recorded a median number of 218 days of activity (interquartile range 86–306). Of these users, 13,332 (43.8 %) entered a valid UK postcode link-able to a postcode district in England or Wales with a corresponding National Statistics Socioeconomic Classification (NS-SEC). Full descriptors of the NS-SEC classes are given in Table 1.

3.1. *Characterising users and app usage*

3.1.1. *Demographic variation in users and app usage*

The number of app users of each age is illustrated in Fig. 1a and Fig. 1b for male and female users respectively. As previously identified, 77.7 % of the app users are female. However, the age distribution of users for both genders is similar, with user numbers greatest for those aged between 25 and 50, and peaking with the highest number of users in their mid 30s. Overall, female users recorded a median of 223 days activity, significantly more than the male app usage median of 194 days ($p < 0.01$). Up to the age of 70, app usage, the average number of days of activity recorded by app users, can be seen to steadily increase with age for both males and females (Fig. 1c and d). The number of users over the age of 70 comprise <0.5 % of the population (91 female users, 60 male users). Therefore, app usage, as depicted in Fig. 1c and d, can be seen to vary significantly in users over 70 due to the smaller sample size. Nonetheless, up until the age of 70, there is a strong positive association between age and app usage (Spearman rank correlation $R^2 = 0.79$ female users and $R^2 = 0.72$ male users).

3.1.2. *Socio-economic variation in app usership*

There is a small but significant difference between the proportion of each NS-SEC class in the postal districts in which Bounts users live versus England and Wales as whole, as shown by the results of the Mann-Whitney *U* test, illustrated in Table 1. The mean percentage of the postal district population who are in NS-SEC classes 1, 2 and 4 are significantly lower for areas in which Bounts users live than England and Wales as a whole. The same is also true for the unclassified proportion of

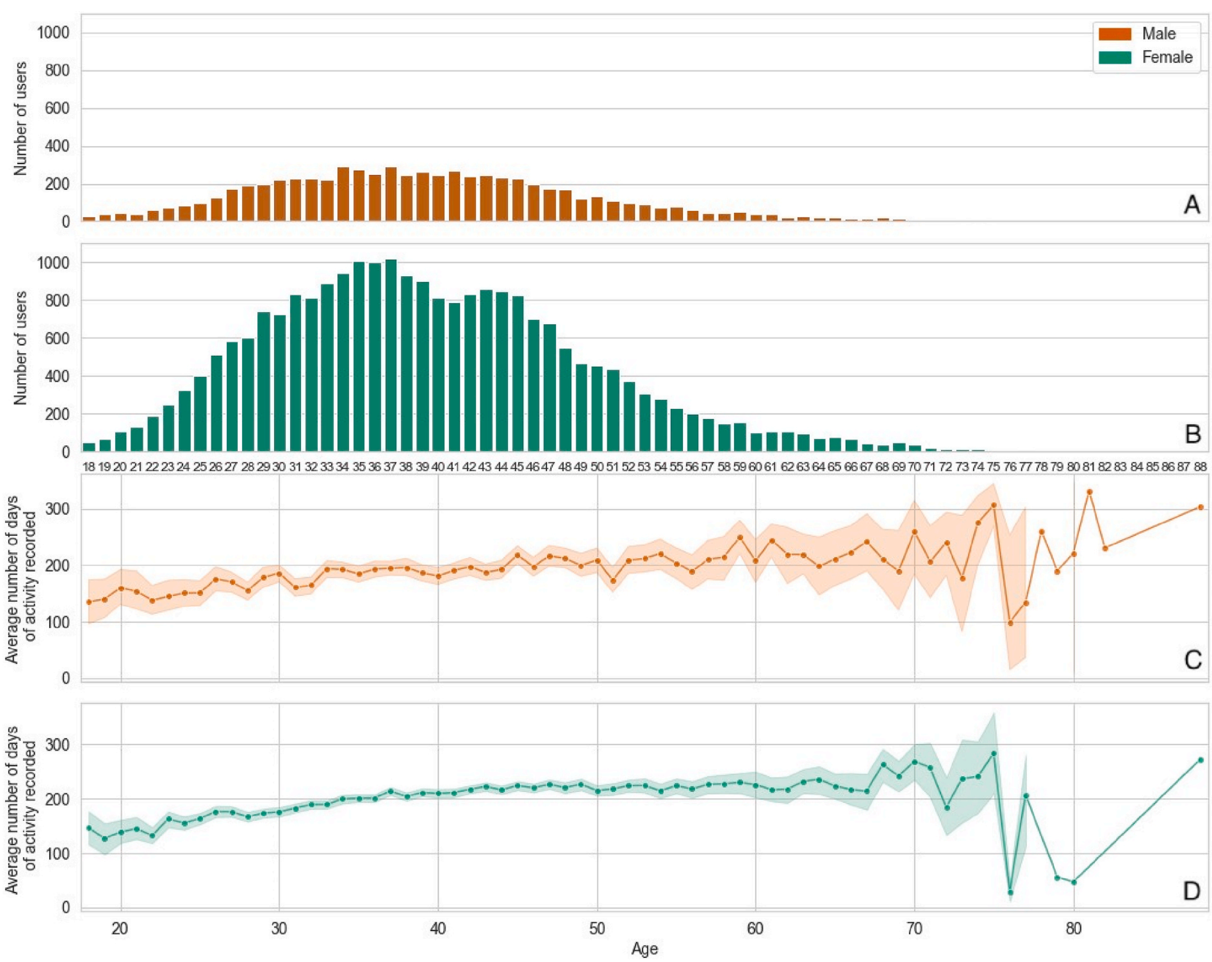


Fig. 1. Number of users of each age (a: Male users, b: Female users). Mean (SD) number of days of activity recorded by app users by age (c: Male users, d: Female users).

the population. Conversely, the mean percentage of the population that are in the less affluent NS-SEC classes (3–8) are all higher than the in the districts in which Bounts users live compared to the population average.

3.1.3. Temporal variation in activity volume

Temporal variations in weekly (weeks 0–52) and annual activity volume are illustrated in Fig. 2a for each day of the week. Grey cells denote days outside of 2016 for weeks 0 and 52. In weeks 12 and 43, the grey cells indicate miscounts associated with UK daylight saving beginning and ending. A notable increase in activity volume, across all days of the week, can be seen following daylight-saving beginning on the Sunday of week 12. This trend tails off slightly around week 24 (mid-June), however, activity volume levels do not drop to pre-daylight saving levels. Activity volume levels again noticeably increase in week 36 (the first week of September) and begin to decrease after daylight saving ends at the end of week 44.

A weekly trend is also evident in Fig. 2a, with higher counts of activity (darker cells on the heat map) earlier in the week. Fig. 2b standardises the weeks by comparing the deviation of each daily activity count from the average number of activities that week. Positive deviations, i.e. day where the number of activities recorded by users is higher than the weekly average, are shaded red, while negative deviations are shaded blue. From Fig. 2b, we can see that Tuesday is consistently the most active day of the week, whilst activity volume on the weekends is on average lower than across the week.

3.2. Characterising physical activity behaviours of app users

General movement, including walking and 'move' activities, were by far the most common activity (68.7 % of activities for male users and 88.4 % for female users) recorded using the Bounts app (Fig. 3a). In contrast, for all other activities, the proportion of women conducting the activity was smaller than the proportion of men for the same activity. For instance, running and cycling activities were more popular with male users than female, with 10.7 % of male activities being classed as running and 7.2 % as cycling, compared to 5.9 % and 1.0 % respectively for female users. Indeed, the raw count of cycling activities undertaken by men exceeds that of women, despite 77.7 % of the Bounts population being female. Similarly, activity popularity varied by age as illustrated in Fig. 3b. Move activities make up a lower proportion of overall activity for those in their mid 30s–50s, whereas cycling and running are more popular than in other age groups. Gym activities are highest in young adults and popularity decreases with age. Caution, again, must be taken when interpreting the proportion of activities undertaken by those aged over 70 due to the small sample size.

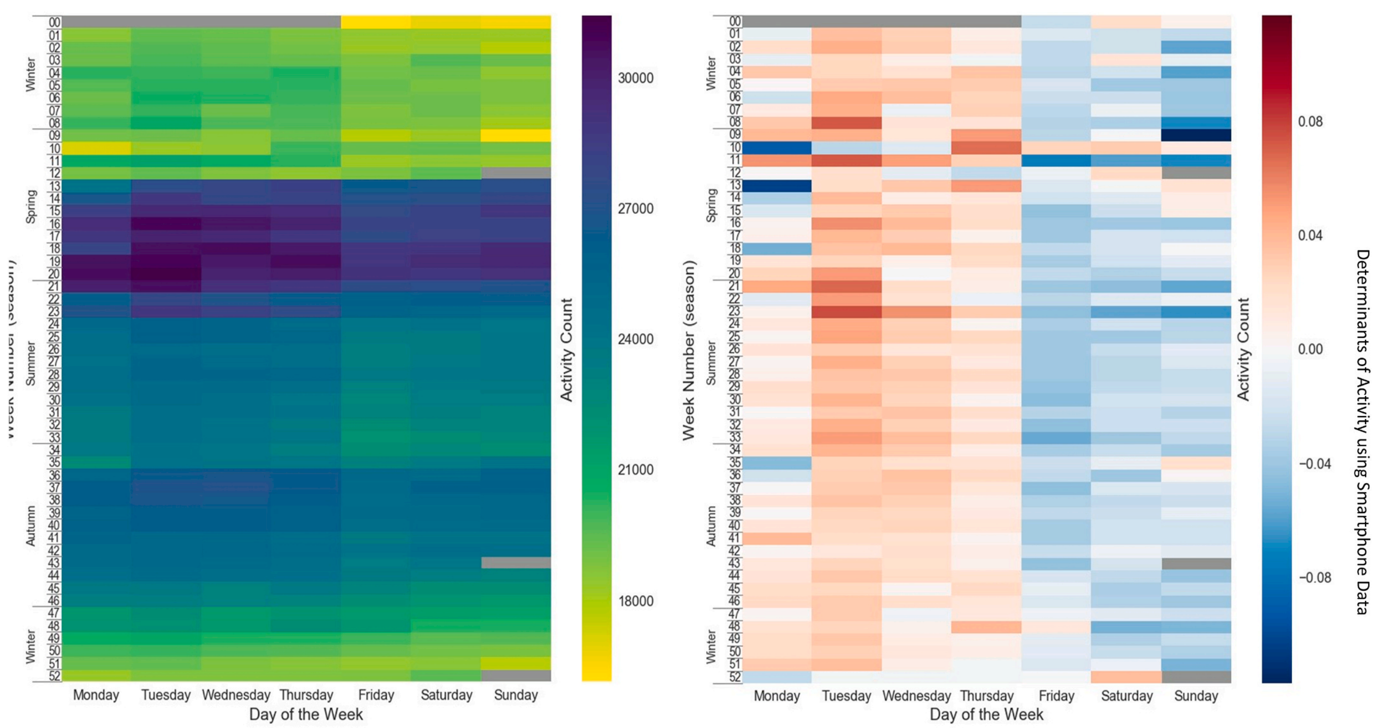
3.2.1. Demographic and socioeconomic variations in physical activity

Variations in physical activity metrics between male and female users were compared and the results are displayed in Table 2. Female users walk significantly fewer steps than their male counterparts. Similarly, male users record both a higher average number of activities a day and a higher average number of different activities whilst using the app. Conversely, female users recorded longer duration activities on average than the male users.

Users living in areas with the highest proportion of NS-SEC class 1 ($\geq$13.6 % of the population) compared to users living in areas which had the lowest proportion of NS-SEC class 1 ($\leq$6.5 % of the population) had a higher average daily step count (5th quintile: 8827 steps, 1st quintile: 8577 steps, $p = 0.015$). Users in areas with highest proportions of NS-SEC 1 also recorded on average (median) marginally more different activity types in a day (5th quintile: 1.08, 1st quintile 1.05, $p < 0.01$), however, they record significantly fewer minutes of activity than the users living in areas with the lowest proportion of NS-SEC 1 (5th quintile:200 min, 1st quintile 230 min, $p < 0.01$).

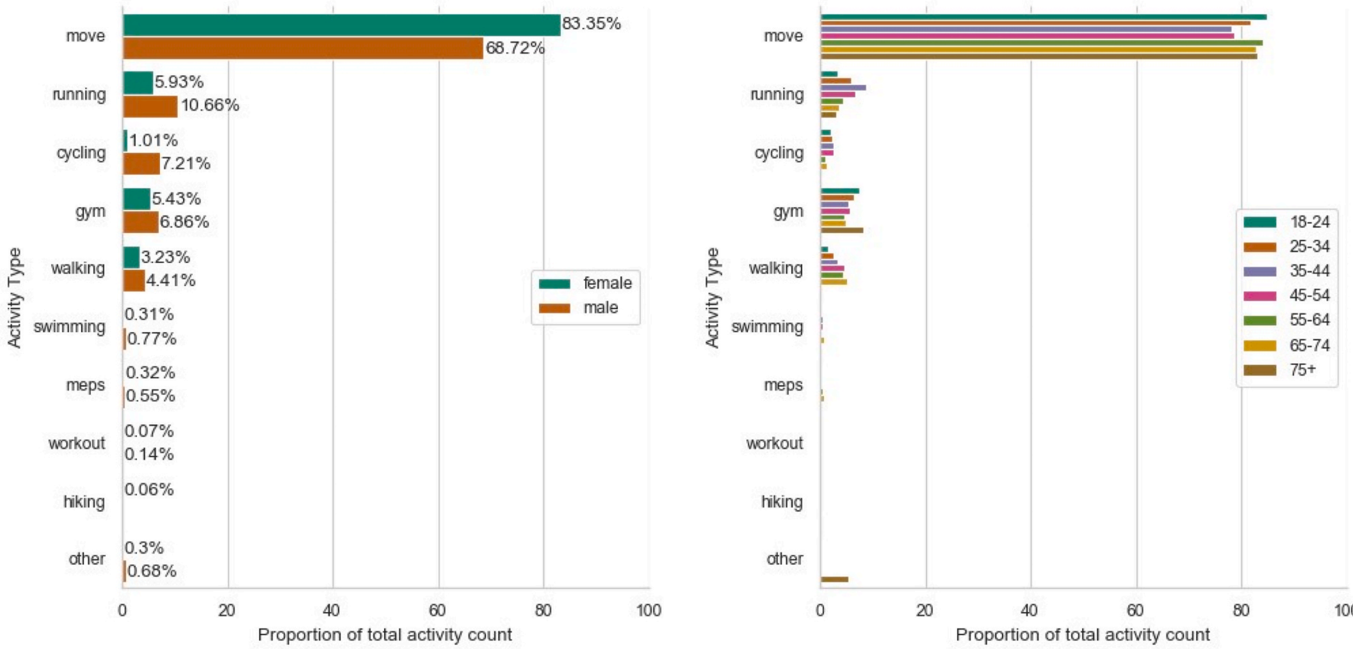
3.2.2. Determinants of meeting physical activity guidelines

Over 1 million weeks of activity were recorded by users, of which 17.5 % of weeks met physical activity guidelines with >150 active minutes recorded, 16.0 % of weeks were classed as insufficiently active, with between 0 and 150 active minutes recorded and 66.5 % of weeks



(a) Number of activities recorded daily across all users for every week in 2016 - raw counts (b) Number of activities recorded daily across all users for every week in 2016 - standardised

Fig. 2. Heatmaps of variations in overall number of activities recorded. (a) Number of activities recorded daily across all users for every week in 2016-raw counts. (b) Number of activities recorded daily across all users for every week in 2016-standardised.



(a) Activity type popularity by gender (b) Activity type popularity by age

Fig. 3. Classification of recorded activity type as a proportion of the total number of activities recorded in 2016 (a) Activity type popularity by gender (b) Activity type popularity by age.

Table 2
Comparison of activity metrics by gender.

Activity Metric		Gender (median) Female	Male	Mann Whitney *U* test for difference (p)
Daily step count		9001	9220	<0.01
Activity duration	All	277	243	<0.01
	Excluding 'move' activities	60	63	<0.01
Number of activities recorded	Average number of unique activity types recorded in 2016 (per user)	1.00	1.008	<0.01
	Average number of different activity types recorded daily (per user)	1.0	2.00	<0.01

had no activity meeting the active minutes criterion. Male and female users both recorded on average 34 weeks of activity.

For each user, the percentage of weeks they met physical activity guidelines was calculated. On average, women met physical activity guidelines (≥150 min) in 12.4 % of the weeks they recorded activity, while male users met guidelines in 24.2 % of weeks. Those in the 35–44 age bracket were most likely to meet weekly PA guidelines with, on average, 17.0 % of weeks meeting the required 150 min. The youngest and oldest users were less likely to meet physical activity guidelines as illustrated by the average values in Fig. 4. The violin plots (Fig. 4) show the distribution of the users by age and gender dependent on what percentage of weeks they achieved the 150-min MVPA guideline. Fig. 4 indicates a large proportion of users did not meet the guidelines for any of the weeks they recorded activity, with a large number of users not recording any weeks which met the guideline of 150 min. This is predominantly due to users who recorded only 'move' activities which could not, due to the daily aggregated data recording, be determined to meet the moderate to vigorous criterion of activity. In terms of NS-SEC classification, those in the top quintile for proportion of NS-SEC class 1, those living in areas with the highest proportion of NS-SEC class 1, met PA guidelines on average 19.3 % of the time, significantly more than those living areas with the lowest proportion of NS-SEC class 1 which met guidelines on average 14.5 % of the time (P < 0.01).

4. Discussion

This study uses the Bounts app data to gain new insight into demographic and socioeconomic variation in physical activity behaviours from and usage behaviours of an incentive based physical activity app. Gender, age and socioeconomic status are all found to be associated with usage of incentive based physical activity. Those in the 30–50 age bracket are most likely to use the app and females are more likely to use the app than males. Moreover, we identify key seasonal and weekly trends in activity volume which captures both app usage and physical activity, with increased activity volume during the months with lighter evenings and higher activity volume mid-week compared to weekends. Socio-demographic variations in physical activity behaviour are also observed for activity duration, volume, variety and activity popularity, resulting in distinct variations in meeting physical activity guidelines. As this is one of the first studies to utilise a large volume of secondary physical activity app data to coinvestigate app usage alongside activity behaviour captured, we evaluate our findings in the context of this novel data source.

When evaluating health and fitness apps for physical activity research, app usership is synonymous with the more traditionally defined participant characteristics. Therefore, characterising app usership is vital in determining the representativeness and applicability of behaviours identified, both in terms of physical activity and app usage behaviours. Interestingly, the Bounts app usership is heavily skewed towards females. Previous literature indicates that physical activity monitoring technology is more commonly used by females than males (Alley et al., 2016). However, males have been found to be more likely to own advanced fitness technology than females (Alley et al., 2016). Griffin and Jiao (2015) and Sun et al. (2017) both found Strava fitness app usership and usage is heavily skewed toward young male users,

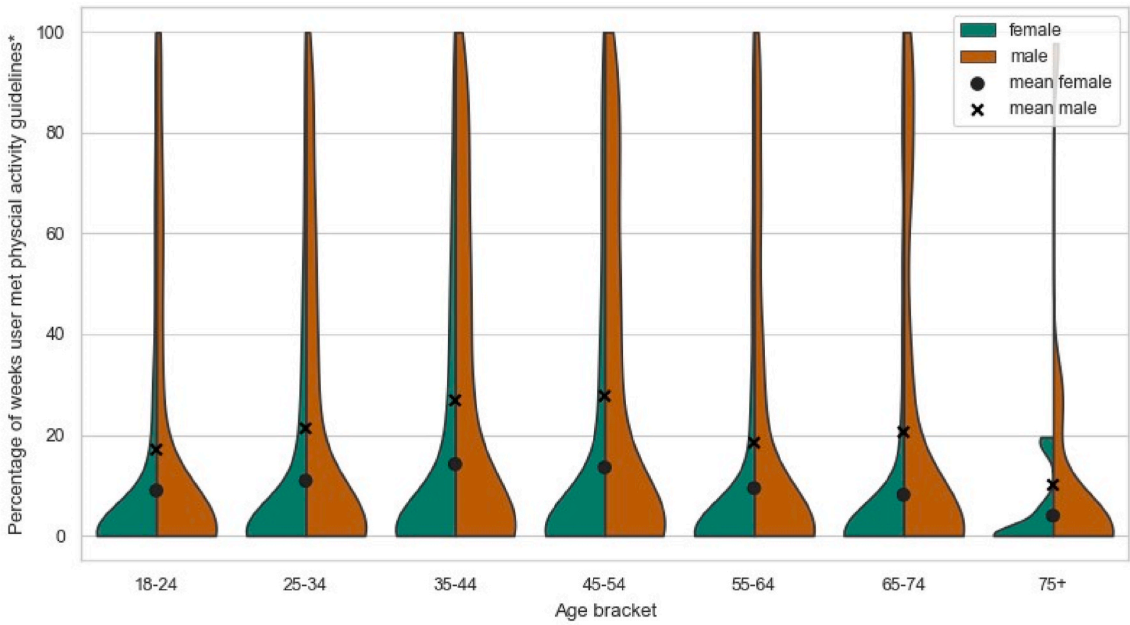


Fig. 4. Distributions of the percentage of weeks users meet the 150 min of moderate to vigorous physical activity guidance by age bracket and gender.

mirroring the trend in advanced fitness technology popularity, accrediting this to the competitive element of the app. Indeed, Kilpatrick et al. (2005) found that men report higher levels of physical activity motivation for competition and challenge than women. We postulate that the high number of female Bounts app users may be in part due to the premise of the Bounts app: to reward activity as opposed to creating competition (which has been shown to attract male users). Mitchell et al. (2017) reported increased app uptake in females for their app which, similar to the Bounts app, incentivises health knowledge. Despite these evident variations, little gender-disaggregated research into physical activity motivation by apps has been conducted to date. Future research could compare Strava user demographics to those of the Bounts users to see if the difference in app premise 'challenge versus reward based' is driving use by different demographic groups. Such observed trends in app premise driving usage have utility in informing research app design to target the desired population group.

App usership is highest in those aged 30–50 for both male and female users. However, there are still a sizeable number of users between the limits of 18 (n = 79) and 70 (n = 45) years of age compared to participant numbers in traditional study designs. An advantage of the Bounts data is the breadth of age of the participants. Often, research investigating physical activity focuses on specific age groups, for example, student populations (Yuan et al., 2015; Lee and Cho, 2017) or older adults (≥50 years of age) (Barnett et al., 2017; Zubala et al., 2017). Some cohort studies only recruit from a specific age range of participants. For instance, UK Biobank participants who recorded physical activity were all 40–69 when recruited (Doherty et al., 2017). Within Bounts users, older age (≥50 years) is associated with increased app usage, with a higher number of average days of recorded activity up to the age of 70, suggesting that adults aged 50–70 who choose to engage with the Bounts app are more committed to continuing to use the app long-term. Seifert et al. (2017) found similar trends in a subset of older adults tracking activity with mobile devices, where the user subset was actively engaged in technology and regularly exercised. Thus, the Bounts app may well be capturing the active, tech savvy older population. However, the number of older adults choosing to initially use the app is fairly small compared to younger adult users.

Compared to England and Wales as a whole, in terms of socioeconomic status, the areas in which Bounts users live have a lower proportion of the population in higher socioeconomic classes. However, the magnitude of difference in terms of socioeconomic status is relatively small, suggesting that the Bounts sample is more representative in terms of socioeconomic status than other physical activity studies where lower socio-economic groups tends to be under-represented (Tjonneland et al., 2007). This is thought to be in part due to volunteer bias, where individuals from lower socioeconomic groups are less likely to volunteer or consent to participate studies (Chinn et al., 2006). Indeed, the UK Biobank cohort study, which has also conducted a large-scale assessment of objectively measured physical activity, reported that participants were less likely to live in more socio-economically deprived areas (Fry et al., 2017). The ability of the Bounts app to capture these hard to reach populations is highly advantageous. As the Bounts app's primary purpose was not research (Supplementary Material A), active participant recruitment was not required and subsequently the issue of volunteer bias is negated, which may explain some of the difference in participant socio-economic status. Previous studies in other fields recognise smart phone technology as a tool for targeting health interventions to lower socio-economic groups (Neubeck et al., 2015). Additionally, the Bounts app offered economic reward in the form of points which could be exchanged for vouchers, which may well be more appealing to those in lower socio-economic groups and occupations. In their meta-analysis, Mantzari et al. (2015) identify higher deprivation status as increasing financial incentive effectiveness in changing habitual health-related behaviours. To avoid ecological fallacy, we can only infer the proportion of the area make up by each NS-SEC socio-economic class and not the definitive socioeconomic status of the users themselves.

Future research utilising smartphone data would benefit from more detailed demographic and location data collection. This would allow sample weightings to be calculated to obtain a representative sample. Moreover, using a finer granularity of geography would enable linkage to other location data such as weather, greenspace and recreational facilities, providing valuable spatial context of the observed physical activity behaviours. Nonetheless, the trade-off between the data security around user identification and data richness must also be considered.

A key strength of the Bounts data is the continuous monitoring of activity over a long temporal period. Only users with at least a week of activity were included, exceeding the usual 7-day cut-off point used in typical case-control studies (Gorman et al., 2014). This advantage allowed us to identify clear weekly and seasonal trends in Bounts app volume (as measured by daily activity count), which captures both app usage and physical activity occurrence. Previous research into seasonal and weekly temporal trends in physical activity have reported mixed results (Tucker and Gilliland, 2007). For instance, Refinetti et al. (2015) observe daily and weekly temporal trends but not monthly or seasonal variation in physical activity of adults across five countries. Similarly, Wang et al. (2017) observed no seasonal variation in activity intensity of participants in China, whilst Hjorth et al. (2013) found daylight levels to be associated with greater physical activity in children. All of these studies, however, were limited by short repeat sampling across the year rather than continuous monitoring of participants, making it difficult to characterise habitual activity behaviour. Secondary smartphone app data allows us to address this monitoring gap with minimal burden on the participant.

Seasonal activity volume variation can be seen with the jump in the number of activities observed after the 27th of March and gradual drop in activity volume after the 30th of October, corresponding with daylight saving beginning and ending. The results suggest daylight saving is playing a role in the volume of activity recorded by users, potentially due to the amount of time available for activity with more daylight in the evenings. Concerns about safety may also play a role in the drop in physical activity with darker evenings, although evidence of the effect of street lighting on physical activity remains mixed (Foster and Giles-Corti, 2008). It is also worth noting this effect will be limited to those countries that observe daylight saving and may well be amplified regionally, dependent on distance from the equator. Hence, different countries may observe different relationships between activity level and daylight. Weather may also compound the effect of this ‘daylight saving effect’, with poorer weather synonymous with the winter months in the UK. With more specific user locations through app GPS data, historic weather patterns would be worthy of investigation, comparing against individual activity levels. The reduction in activity volume with the return to standard time from summertime, and corresponding drop in evening daylight is an important public health policy consideration (Goodman et al., 2014) that warrants further in-depth analysis of long-term temporal activity data. Though the advantages of daylight saving are mixed and complex, with the abolishment of daylight saving in EU states as of 2021, population physical activity levels should be considered when choosing to permanently switch to standard or summertime.

By controlling for week-to-week variation in calculating the absolute deviation in the number of daily activities recorded from the weekly average, we demonstrate a clear weekly trend in activity volume, with weekends consistently producing the lowest number of activities recorded and lower steps counts across all users, and the highest activity counts being seen on a Tuesday. With shorter duration studies, these trends may not be observed or may be masked by other influences on activity levels. This midweek peak suggests that the traditional working week is a key factor in activity behaviours. Indeed, this may be due to more functional activity being conducted, e.g. active commuting, or that routine recreational activity is more commonplace during the more structured working week. This also contradicts the ‘weekend warrior theory’ that individuals exercise more intensely and frequently on the weekend (Kruger et al., 2007). The proportion of the Bounts population from areas with a higher proportion of the population from lower socioeconomic status groups, compared to traditional studies, may play a role in the lack of a weekend warrior phenomena; Shuval et al. (2017) theorise lower socioeconomic status participants are less likely to be weekend warriors compared to their wealthier counterparts. Previous studies investigating this weekend warrior phenomenon tend to utilise survey data (Shiroma et al., 2019), suggesting potential for under reporting of habitual activity mid-week; however, this data is captured by wearables or smartphone sensors. Future work looking to characterise individual level activity patterns in physical activity and app usage behaviour would help unravel these patterns further.

Meeting the physical activity guideline of 150 min of moderate to vigorous activity (MVPA) has many well-established benefits to health, yet the proportion of Bounts users meeting the required threshold is low. Of the weeks Bounts users recorded activity, only 15.3 % met the threshold of at least 150 min of MVPA. However, 47.0 % of users met physical activity guidelines at least once, with 53.0 % of users only recording ‘move’ activities where the intensity could not be determined. In comparison, the Health Survey for England (HSE), which surveys a representative population sample and calculates the average weekly activity over a four week recall period, found 66 % of men and 58 % of women over the age of 16 met the same MVPA guidelines in 2016 (Scholes, 2017). This disparity between meeting MVPA guidelines may be due to both the criteria used to define moderate to vigorous physical activity, as well as recall period and demographic characteristics of the two studies. Compared to the HSE representative sample, Bounts usage is heavily female biased. In their analysis of the 2012 Roberts et al. (2016) found that female respondents were significantly less likely to meet MVPA guidelines. Therefore, the proportion of weeks’ activity meeting guidelines would be expected to be lower for Bounts users than the HSE respondents. From the Bounts activity data, we can in part accredit this lower likelihood of meeting MVPA guidelines to these female users having marginally lower average step counts and partaking in significantly fewer activity types than men. However, female users record significantly longer duration of activities (30 more minutes per day) and prefer ‘move’ activities over males. This suggests that female users may be less likely to meet the moderate intensity of activity threshold, although they are still active throughout the day and spend less time sedentary than male users, mirroring a range of studies which found female gender to be inversely related to sedentariness (O’Donoghue et al., 2016). A similar pattern in reduced activity variety and likelihood of meeting physical activity guidelines but increased activity duration is seen when comparing areas with the highest and lowest percentile of NS-SEC 1 users; individual level socioeconomic data would be of great value to explore this further. As previously mentioned, the Bounts activity is likely to miss some activity due to the user not carrying their phone during the activity. Moreover, some of the ‘move’ activity may well be classified as moderate to vigorous, i.e. brisk walking, but as the data metrics are aggregated across the day, it is impossible to work-out the time, if any, spent briskly moving. It is also possible that brisk walking was misreported by HSE respondents as the definition of brisk may vary from individual to individual, or indeed, all exercise may be incorrectly estimated due to social desirability bias to appear more active.

Physical activity plays an important role in preventing both communicable (Sallis et al., 2020) and non-communicable disease, such as obesity, coronary heart disease and diabetes (Butland et al., 2007). Thus, increasing the physical activity levels of inactive populations remains at the forefront of health policy (Department of Health and Social Care, 2019). Whilst the Bounts app does capture data from a large demographic range, the sample captured is not representative of the population as a whole, limiting the generalisability of the observed temporal patterns and physical activity behaviours. As identified by Hicks et al. (2019), much of the challenge of using secondary physical activity app data usage is the inherent ‘messiness’ as they are not designed for the specific addressing of the research question. Further validation work using more traditional methodologies alongside smartphone data is required, as well as further investigation of these behaviours using other secondary physical activity data sources. Nonetheless, these secondary smartphone data not only provide us with an in-depth longitudinal insight into physical activity behaviours and indicate the drivers of individual physical activity engagement, they also contribute insight into other health behaviours such as sleep quality, fertility and heart health. App premise, usership and popularity all need careful investigation and consideration before applying observed physical activity behaviours to the general population. Yet, used appropriately, these secondary data can serve as a substantial piece of the rich data jigsaw in a whole systems approach to tackling noncommunicable disease.

5. Conclusions

Utilisation of secondary physical activity and fitness app data it still in its infancy. Through our novel analysis of Bounts app data, we demonstrate the valuable insights into activity behaviours these smartphone app data can provide. In summary, we observe key differences in activity behaviours between men and women, resulting in women less likely to meet physical activity guidelines. We also note key differences in engagement and usage of activity tracking apps with age and socioeconomic status. Additionally, we identify new seasonal and weekly patterns in activity behaviour. These insights are possible due to the potential of secondary data to capture physical activity behaviours of a wider population at a large scale and over a longer temporal period than traditional methods, with no participant burden. These secondary app data are not without their limitations, for instance in the case of Bounts data, we are unable to unpick the role of incentives in selection bias and influence on physical activity behaviours. Yet by realising both the strengths and limitations of these secondary app data, we can utilise them to further our knowledge of physical activity behaviours. Future work should look to calibrate these secondary data against more traditional methods, conduct cross-app analysis to further our insights into the activity behaviours captured, and develop more robust methods of physical activity data cleaning and analysis.

Credit statement

Francesca Pontin: Conceptualization, Data curation, Methodology, Software, Validation, Formal analysis, Visualisation, Writing – original draft & Writing – review & editing, Nik Lomax: Supervision, Conceptualization, Funding acquisition, Writing – original draft and Writing – review & editing, Graham Clarke: Supervision, Conceptualization, Funding acquisition, Writing – original draft and Writing – review & editing, Michelle Morris: Supervision, Conceptualization, Funding acquisition, Writing – original draft and Writing – review & editing.

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Appendix A. Supplementary data

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