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Investigating the environmental, behavioural, and sociodemographic determinants of attendance at a city-wide public health physical activity intervention: Longitudinal evidence over one year from 185,245 visits

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Investigating the environmental, behavioural, and sociodemographic determinants of attendance at a city-wide public health physical activity intervention: longitudinal evidence over one year from 185,245 visits

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Abstract

Understanding the determinants of attendance at public health interventions is critical for effective policy development. Most research focuses on individual-level determinants of attendance, while less is known about environmental-level determinants. Data were obtained from the Leeds Let's Get Active public health intervention in Leeds, England. Longitudinal data (April 2015–March 2016) on attendance were obtained for n=25,745 individuals (n=185,245 total visits) with baseline data on sociodemographic determinants and lifestyle practices obtained for n=3,621 individuals. This resulted in a total of n=744,468 days of attendance and non-attendance. Random forests were used to explore the relative importance of the determinants on attendance, while generalised linear models were applied to examine specific associations (n=3,621). The probability that a person will attend more than once, the number of return visits, and the probability that a person will attend on a particular day were investigated. When considering if a person returned to the same leisure centre after one visit, the most influential determinant was the distance from their home. When considering number of return visits overall however, age group was the most influential. While distance to a leisure centre was less important for predicting the number of return visits, the difference between estimates for 300m and 15,000m was 7–10 visits per year. Finally, calendar month was the most important determinant of daily attendance. This longitudinal study highlights the importance of both individual and environmental determinants in predicting various aspects of attendance. It has implications for strategies aiming to increase attendance at public health interventions.

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1. Introduction

Healthy lifestyles are central to wellbeing (1). Exhibiting unhealthy behaviours heightens the risk of non-communicable diseases and mortality and, can elicit multiplicative negative effects (2, 3). Implications of this are profound given the regularity with which unhealthy lifestyle practices co-occur (2-5). Health-related policy and health improvement interventions have not provided viable solutions, particularly for deprived communities (6). Consequently, socially disadvantaged individuals tend to engage in detrimental health behaviours more frequently due to a myriad of social, environmental, and behavioural determinants (7). Moreover, unhealthy lifestyle practices (e.g. lack of physical activity, smoking, diet and alcohol) have been described as the most direct risk factors for many non-communicable diseases (8), and are among the leading causes of health loss (9). Understanding factors associated with successful implementation of public health interventions, is therefore fundamental for public health systems wishing to be successful, sustainable, and tackle inequalities (10). Evaluation of attendance at such interventions is seldom carried out using large-scale measurement data, and is often limited by sample size or geographical area with only cross-sectional or few observations (11).

While evidence often focuses on the sociodemographic determinants of attendance at public health interventions, environmental determinants may also impact attendance (12). Wider structural, economic and cultural determinants such as a fear of stigma (13), lack of flexibility in opening hours (14), or irregular working hours (15, 16) may lead to poor adherence or retention. Considering wider determinants is especially important for interventions aimed at increasing physical activity (17), where day length and weather conditions are key determinants for participation (17-20); winter months when the weather is cold and wet, and the evenings are dark, generally demonstrate the lowest activity levels (21, 22). Equally, excessive heat and humidity negatively impact participation (22). Although, unpleasant weather conditions (23) and an individual's age (24) influence physical activity participation outdoors, less is known about how these determinants influence participation in indoor exercise (17). Indoor opportunities during unfavourable weather conditions may help foster regular physical activity habits, especially among chronically inactive individuals who may struggle to participate in health enhancing physical activity practices (19). However, a review found little support for the presumed environmental determinants of attendance and physical activity behaviour (25). Consequently, a better understanding of both individual- and environmental-level determinants of attendance at public health interventions is required.

Emerging evidence is limited but seems to highlight the importance of proximity, with uptake generally greater among individuals who live closer to facilities (26-28). Participants with ≥4 exercise facilities in their neighbourhood are estimated to spend five more minutes in moderate to vigorous physical activity (MVPA) per day compared to those with no exercise facilities (28). Further, research shows that individuals living closer to a supermarket had significantly higher fruit and vegetable consumption (29). Nevertheless, proximity is not immune to inequalities; individuals in more affluent areas are estimated to have greater access to public health services, and the social and economic capital to attend them (30). Moreover, a greater concentration of fast-food outlets in home neighbourhoods are

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associated with an increased consumption of fast-food, especially in lower socioeconomic areas (31, 32). Similarly, a greater availability of physical activity facilities and greenspace were associated with a lower risk of obesity only among the most affluent (33). Finally, while a recent UK-based longitudinal study found inverse associations between park access, fitness facilities and body weight outcomes, these were only observed for younger adults (33). Thus, it is plausible that the influence of environmental determinants on attendance varies by age (34). Yet, the interplay between individual- and environmental-level determinants are seldom explored.

This study aims to address this knowledge gap by examining whether the interplay between individual-level determinants, environmental-level determinants and environmental conditions are likely to be important factors in policy-making. We investigate the influence of proximity, the weather and seasonality, and lifestyle practices on attendance at a citywide public health intervention for physical activity over the course of one year. We hypothesise that longer distance and worse weather will decrease the likelihood of attendance. We also examine differences in associations between environmental determinants and attendance by age, gender and socioeconomic status.

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2. Methods

2.1 Study background

The Leeds Let's Get Active (LLGA) intervention (35) is a community-based public health intervention that encourages inactive Leeds residents to "do more activity". Participants engaging in the scheme had free access to 15 Leeds City Council leisure centre swimming pools and gyms on specified days and times. Each week approximately 150 one-hour long timetabled sessions – predominantly off-peak – were available across the participating sites. Recruitment was open to all adults in the local area (Yorkshire, UK). Ethical approval was obtained through Leeds Beckett University research ethics committee.

2.2 Study population

Participants were recruited between April 2015 and March 2016. Anyone who registered or attended LLGA within this time was included in the overall sample, which contained n=25,745 people and n=185,245 total visits. Data from n=6,598 participants were excluded based on age (i.e. under 16 years), and data from n=5 participants were removed where distance from a residential postcode to an attended LLGA session exceeded 100 kilometres (62.1 miles). The final sample included n=19,142 participants, who registered n=159,086 total leisure centre visits within the study period.

2.3 Measures and data capture

2.3.1 Attendance

Attendance data, date of visit, venue, and the type of session attended were captured using membership card. Associated to a participant's membership number/card were data pertaining to their age, gender and residential postcode.

2.3.2 Demographics and lifestyle practices

Participant data was collected at baseline via an online survey. Demographics were obtained in relation to age, ethnicity, deprivation, employment, education and marital status. Area-level deprivation was based on the Index of Multiple Deprivation for the lower super output area of residence and how this ranked within Leeds. These were classified in line with local guidance into the following categories: 1) not a deprived area, 2) top 3% most deprived areas in Leeds, 3) 4–10% most deprived areas in Leeds, and 4) 11–20% most deprived areas in Leeds. For lifestyle practices, participants were asked to self-report their amount of MVPA over the preceding week (36, 37). Based on UK physical activity recommendations (38), participants failing to meet the equivalent of ≥150 minutes MVPA were categorised as being insufficiently active, and those achieving <30 minutes MVPA as inactive (39). Diet was assessed by summing fruit and vegetable portions (≥100g) consumed by participants on a typical day. To follow UK policy guidance, participants were deemed to have an unhealthy diet if they ate less than five portions per day (40). Alcohol consumption was measured using the brief screening tool, AUDIT-C (41). Participants were also asked about their smoking habits, with current smoking categorised as an unhealthy practice (42). Participants' height

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and weight were also self-reported to calculate body mass index (BMI). To assess subjective wellbeing, participants were asked how satisfied they were with their life and how happy they felt (43). The above data was collected at baseline for n=5,280 participants who registered from April 2016. Only selected demographic and lifestyle practices were recorded for participants who registered prior to this date.

2.3.3 Weather conditions

Longitudinal weather data for April 2015–March 2016 was sourced from the National Centre for Atmospheric Science, Leeds weather station. The station uses a VantagePro2, controlled by 'weewx', an experimental weather software system written in Python. Data was collected for maximum, minimum and mean daily temperature (Celsius), daily average wind speed (mph), and daily rainfall (mm).

2.3.4 Proximity

The dataset contained n=159,086 recorded visits (origin and destination) and was geocoded in ArcGIS Online, providing latitude and longitude coordinates. Ordnance Survey Open Roads was used to model the road network distance from a participant's home to a leisure centre intervention site. Network distance was calculated using ArcGIS Origin-Destination (OD) Cost Matrix (Network Analysis extension) with home sector postcode as the origin and LLGA facility postcode as the destination.

2.3.5 Study area

Leeds is a large city in West Yorkshire, in the north of England, UK (Figure 1). Recent estimates (2018) show a total population of 789,194 in the metropolitan district.

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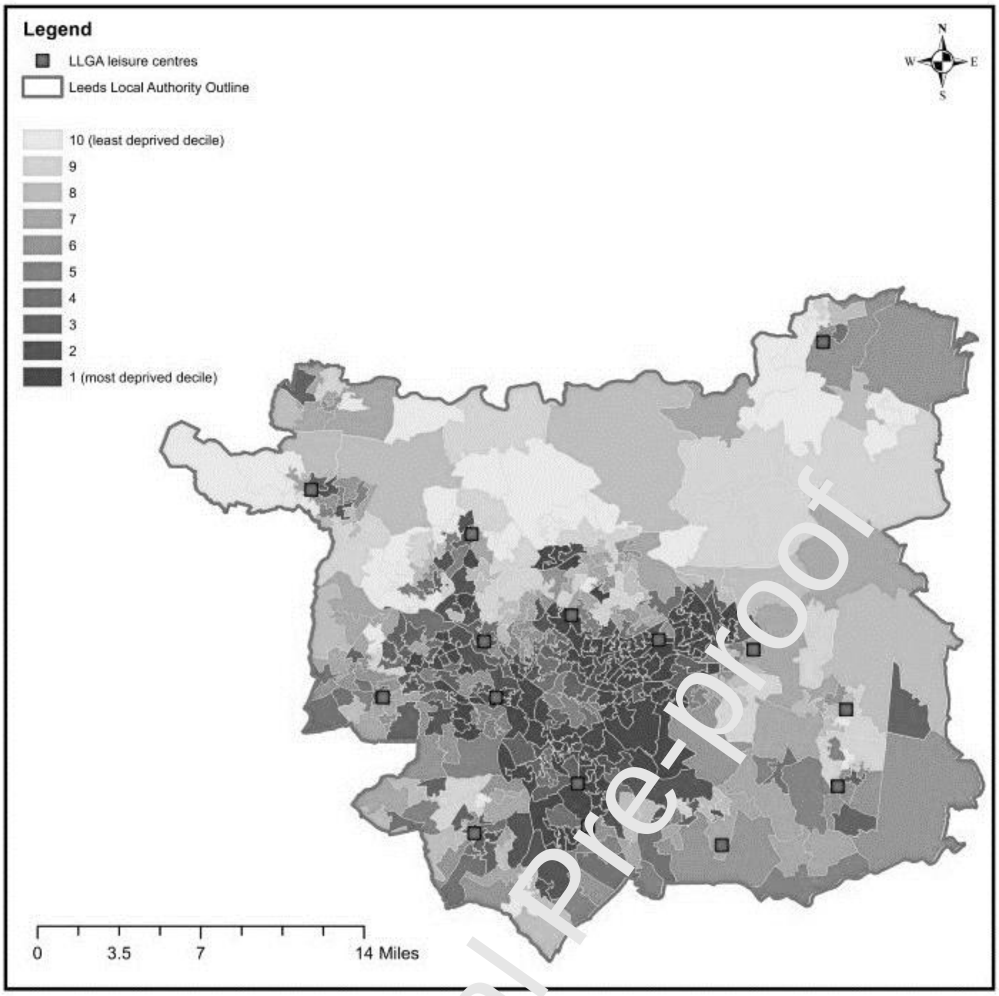

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Figure 1. Map showing the location of the study area and LLGA leisure centres alongside the 2015 Index of Multiple Deprivation.

2.4 Statistical analyses

Independent t-tests and one-way ANOVA were used to study differences in proximity and weather conditions for visits by venue, type of session (pool or gym), and meteorological season. For each participant, the number of days "available" for return visits was defined as the number of days remaining in the study year after the first visit, resulting in n=744,468 return days. Regression models typically used to model complex interactions between a large number of potential predictor variables or covariates are based on fairly strict assumptions and often are not suitable for complex multivariable datasets (44). Therefore, we applied a machine learning technique – random forest – to analyse the effects of weather and demographic factors on leisure centre attendance. The random forest technique focuses on three aspects: 1) the probability that a person will make a return visit, 2) the number of return visits, and 3) the probability that a person will attend a leisure centre on a particular day. We focused on key environmental determinants such as distance to a leisure centre, weather and month. We then explored differences in the likelihood of attendance by age group and gender. Although flexible, this technique does not produce easily interpretable linear coefficients or p-

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values. Instead we report the relative importance of the variables, their effect on Mean Squared Error (MSE), and prediction accuracy. To illustrate the effect size, we show what would happen to the sample if the relevant covariates (e.g. age, gender, ethnicity, employment status, and happiness) for all the people in the sample were to change to the level of interest. For example, incrementally changing the distance to the nearest facility from 300m to 15,000m while keeping other variables unchanged. In addition, we fitted generalised linear models to obtain effect estimates [95% confidence intervals]. Given the size of the dataset, most effects are expected to be statistically significant, even when very small. All statistical analyses were carried out in R (45).

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3. Results

3.1 Descriptive statistics

The following analyses are based on n=19,142 participants attending a LLGA session between April 2015 and March 2016. Table 1 shows that 59.3% of participants were female and the average age was 39 (±15.6) years. More than three quarters of participants were from a white British ethnic background and 61.0% lived in a postcode classified as not deprived.

Table 1. Demographic characteristics of LLGA participants

DEMOGRAPHICS	PROPORTION	NUMBER
Gender (n=19,142)		
Female	59.3%	11,352
Male	40.5%	7,749
Prefer not to say	0.2%	41
Age (n=19,142)		
15–24	19.3%	3,703
25–34	26.9%	5,142
35–44	22.6%	4,334
45–54	12.7%	2,435
55–64	10.2%	1,948
65+	8.[illegible]%	1,580
Area-level deprivation (n=5,280)		
Not deprived area	61.0%	3,219
Top 3% most deprived areas in Leeds	23.5%	1,240
4–10% most deprived areas in Leeds	10.0%	526
11–20% most deprived areas in Leeds	5.6%	295
Ethnicity (n=5,280)		
White British	76.1%	4,017
Asian/Asian British	6.9%	363
Black/Black British	5.1%	269
Other	11.9%	631
Employment status (n=5,280)		
Full-time paid employment	40.0%	2,114
Part-time paid employment	20.2%	1,066
Unemployed	16.7%	884
Student	9.9%	524
Retired	7.9%	418
Other	5.2%	274
Academic (n=5,280)		
No qualifications	16.2%	854
GCSE/O Level grade A- C*	28.8%	1,521
A Levels/Diploma in HE	26.4%	1,392
First degree (BSc, BA)	21.5%	1,134
Higher degree (MSc, PhD)	7.2%	379
Marital status (n=5,280)		
Married	39.7%	2,097
Single	32.5%	1,716
Cohabiting	18.5%	977
Divorced/separated	4.0%	213
Other	5.3%	277

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3.2 Lifestyle practices and environmental data

At baseline, 86.7% of participants were not meeting the physical activity guidelines, 81.6% ate <5 portions of fruit and vegetables each day, 16.1% were current smokers, and 45.5% presented hazardous or harmful alcohol use (Table 2).

Table 2. Lifestyle practices undertaken by participants

LIFESTYLE PRACTICE	PROPORTION	NUMBER
HEPA category (n=12,541)		
Inactive (<30 mins MVPA/week)	44.9%	5,633
Insufficiently active (30–149 mins MVPA/week)	41.3%	5,244
Achieve physical activity guidelines	13.3%	1,664
Daily fruit and vegetable consumption (n=5,280)		
None	7.8%	411
1–4 portions	73.8%	3,898
5 or more portions	18.4%	971
Current smoking status (n=5,280)		
Never smoked	58.4%	3,081
Former smoker	25.5%	1,349
Current smoker	16.1%	850
Weekly alcohol consumption (n=5,280)		
Don't drink alcohol	21.4%	1,130
Drink alcohol responsibly	33.1%	1,746
Excessive consumption	45.5%	2,404
Weight category (n=3,840)		
Underweight	2.7%	105
Healthy weight	45.3%	1,741
Overweight	29.6%	1,136
Obese	22.3%	858
Diagnosed with a long-term condition (n=5,280)		
No	82.9%	4,379
Yes	17.1%	901

HEPA = Health enhancing physical activity

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Table 3 shows the summary data for each visit in the study period. The attendance figures for the 15 venues varied considerably, with Venue 1 having more than twice as many visits as any other centre. The average distance from residential postcodes also showed sizable variation (p<0.001), with figures ranging from approximately 2.5km to 6km. Swimming was more popular than gym sessions and the average distance from participants' residential postcodes was significantly higher for swimming compared to gym sessions (p<0.001). Also, swimming was attended when the daily temperature was significantly higher (p<0.001), and wind speed (p<0.001) and rainfall (p<0.001) were significantly lower. The summer months, when the average temperature was highest and average rainfall lowest, generated the most visits. Post hoc analyses showed that spring and summer generated visits with significantly shorter average distances compared to winter (*p*<0.001) and autumn (*p*<0.001).

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Table 3. Weather and distance from residential postcode by venue, session type and season

	NUMBER OF VISITS	AVG DIST (meters)	AVG TEMP (C)	AVG WIND (mph)	AVG RAIN (mm)
Total	*159,086*	*3,787.6*	*10.66*	*4.10*	*0.79*
Venue					
Venue 1	32,181	3,150.9	10.89	4.06	0.76
Venue 2	14,494	4,893.9	10.77	3.99	0.79
Venue 3	13,082	2,624.0	10.75	4.06	0.73
Venue 4	12,342	3,812.5	10.49	4.24	0.86
Venue 5	12,232	4,454.2	10.52	4.19	0.84
Venue 6	12,297	2,719.4	10.89	4.07	0.77
Venue 7	10,684	5,473.0	10.48	4.11	0.83
Venue 8	10,068	4,729.8	10.38	4.17	0.81
Venue 9	9,272	3,015.8	10.71	4.08	0.78
Venue 10	7,481	4,083.6	10.51	4.14	0.82
Venue 11	6,694	3,483.5	10.51	4.13	0.77
Venue 12	6,422	2,569.3	10.46	4.13	0.78
Venue 13	6,140	3,593.6	10.52	4.11	0.79
Venue 14	4,600	6,044.6	10.42	4.19	0.84
Venue 15	1,097	6,091.1	10.90	4.07	0.89
Session type					
Swimming	84,327	3,969.6	10.75	4.07	0.77
Gym	73,144	3,542.8	10.53	4.15	0.80
Season					
Spring	39,039	3,685.5	8.82	4.13	0.73
Summer	42,170	3,738.6	15.63	3.54	0.65
Autumn	38,516	3,841.3	11.15	3.53	1.00
Winter	39,361	3,888.9	6.67	5.25	0.78

Data are reported to two decimal places for temperature, wind and rain.

3.3 Exploring the relative importance and associations between attendance, sociodemographic, lifestyle practices, and environmental determinants

The full range of sociodemographic and lifestyle practice variables were available for the smaller subset of the dataset (n=3,621). We transformed this, resulting in a total of n=744,468 days available for return visits to a leisure centre. Overall, n=15,067 visits were made, translating to an average of 7.4 visits per year. A total of 37.3% participants attended once (the full distribution of the number of visits per person is shown in Figure S1, supplementary materials). This section assesses the probability that a person will return (i.e. go more than once), the number of return visits, and that a person will attend a leisure centre on a particular day. We focus on key environmental determinants such as the distance to a leisure centre, weather and month. We then explore differences in the likelihood of attendance by age group, gender and socioeconomic status.

The distance to a leisure centre from home was found to be the single most influential variable to predict the probability of at least one follow-up visit (Figure 2; Panel 2A). However, the effect of this distance on the expected probability of at least one return visit varied by demographics (Figure 2; Panel 2B). Distance to a leisure centre only seems to have an effect beyond approximately 5km, where most groups showed a declining trend. When we explored differences by age, gender and socioeconomic status, distance seemed to have almost no influence on men aged 65 or over. In other analyses (Figure S2, supplementary materials), there was little difference by deprivation.

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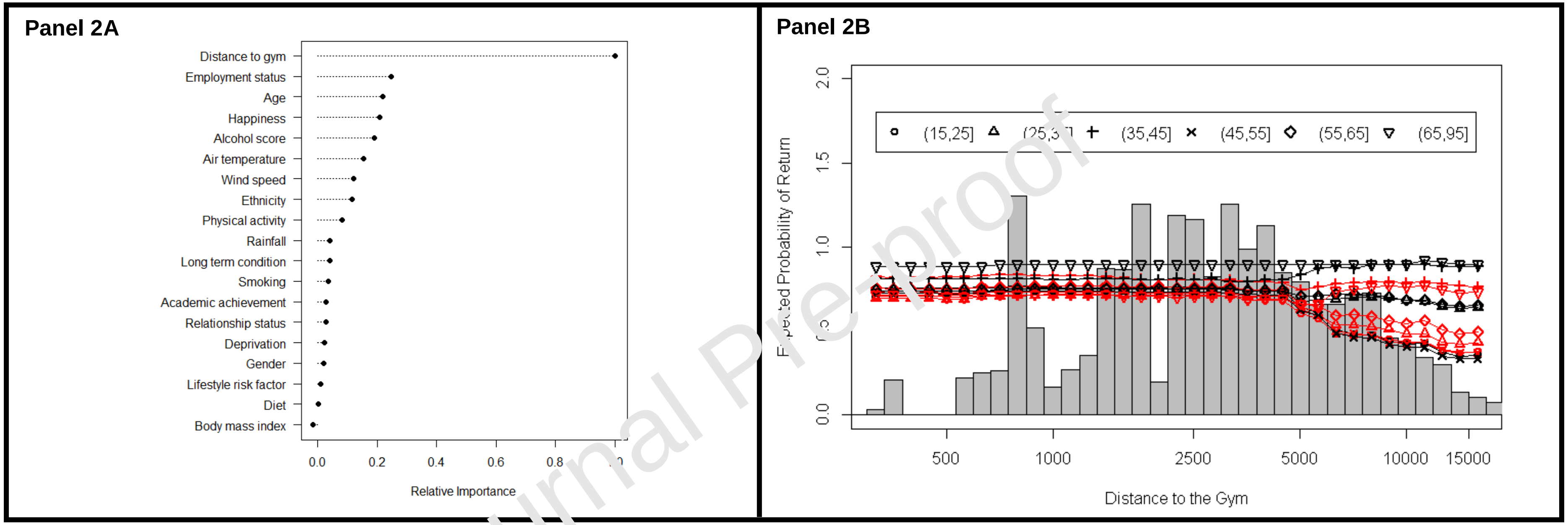

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Figure 2. Panel 2A shows the relative importance for the probability of return visits of sociodemographic, lifestyle practices, and environmental variables (on the day of the first visit). Panel 2B shows the expected probability of a return to the leisure centre for the observed sample, conditional on the distance to the leisure centre by gender (black = women, red = men) and age (symbol: **O** [15 to <25 years]; △ [25 to <35 years]; **+** [35 to <45 years]; **x** [45 to <55 years]; ◇ [55 to < 65 years]; ▽ [65 years and over]). The histogram in grey shows the current distribution of leisure centre distances for the sample.

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Figure 3 (Panel 3A) shows that age group was the single most important predictor of the number of return visits. In order to assess the size of the effect of distance to a leisure centre on the expected number of visits per year, we used the model to predict the expected number of visits per year if the entire sample was living within a certain distance from a leisure centre. We varied this distance from 300m to 15,000m and recorded the minimum and maximum predicted number of visits per year. The results, stratified by age and gender, are shown in Figure 3 (Panel 3B). For distance to a leisure centre, the difference between the estimates for 300m and 15,000m was 7–10 visits per year, approximately 1 extra visit every 6 weeks. For example, as shown in Figure 3B, for younger groups, the variation in distance to a leisure centre can increase the number of visits from approximately 10 to 15 while for a 45–55 year old woman this can range from approximately 20–30. Other things being equal, men tended to have more return visits than women, and older people tended to have more return visits than younger people.

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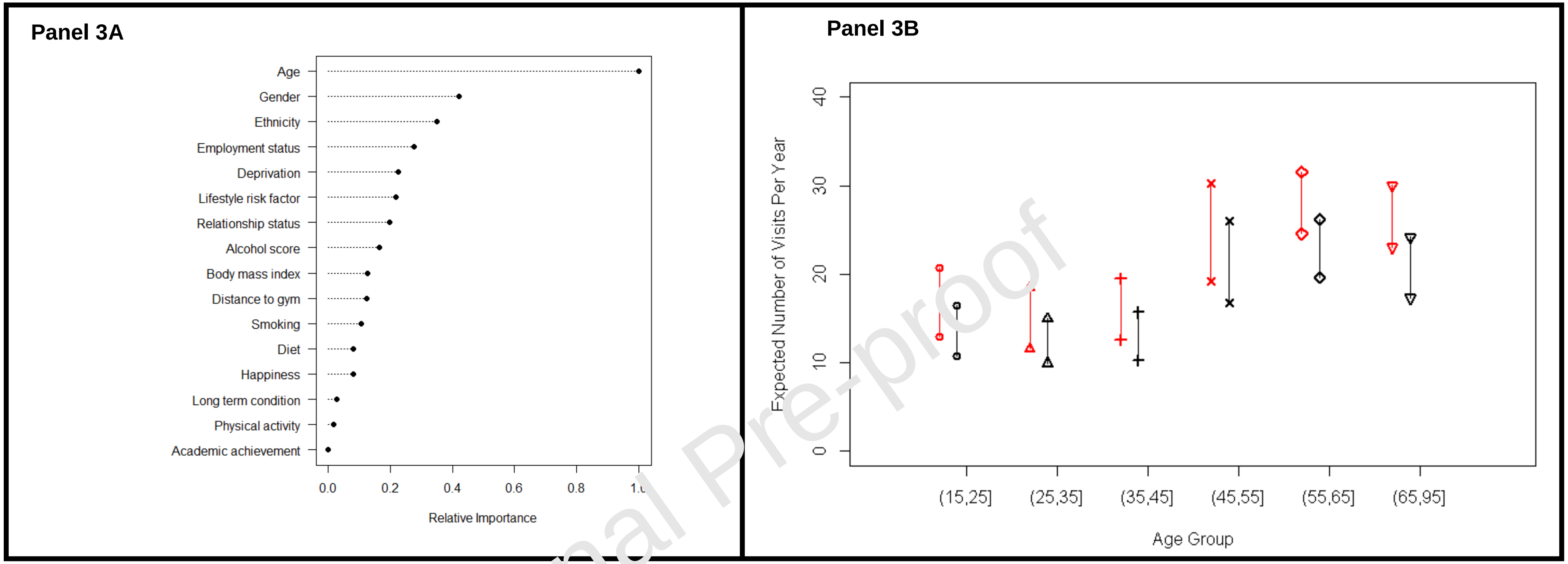

Figure 3. Panel 3A shows the relative importance of variables when predicting the number of return visits. Panel 3B highlights the range of expected number of return visits per year for men (red) and women (black) by age group (years) as the distance to a leisure centre varies from 300m to 15,000m.

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We also assessed the effect of environmental variables on if a visit was made on a particular day. Overall, the random forest model had a better fit when it did not include weather. Calendar month was the most significant predictor of attendance, with summer being more popular than winter (Figure 4; Panel 4A). There were few differences by area-level-deprivation.

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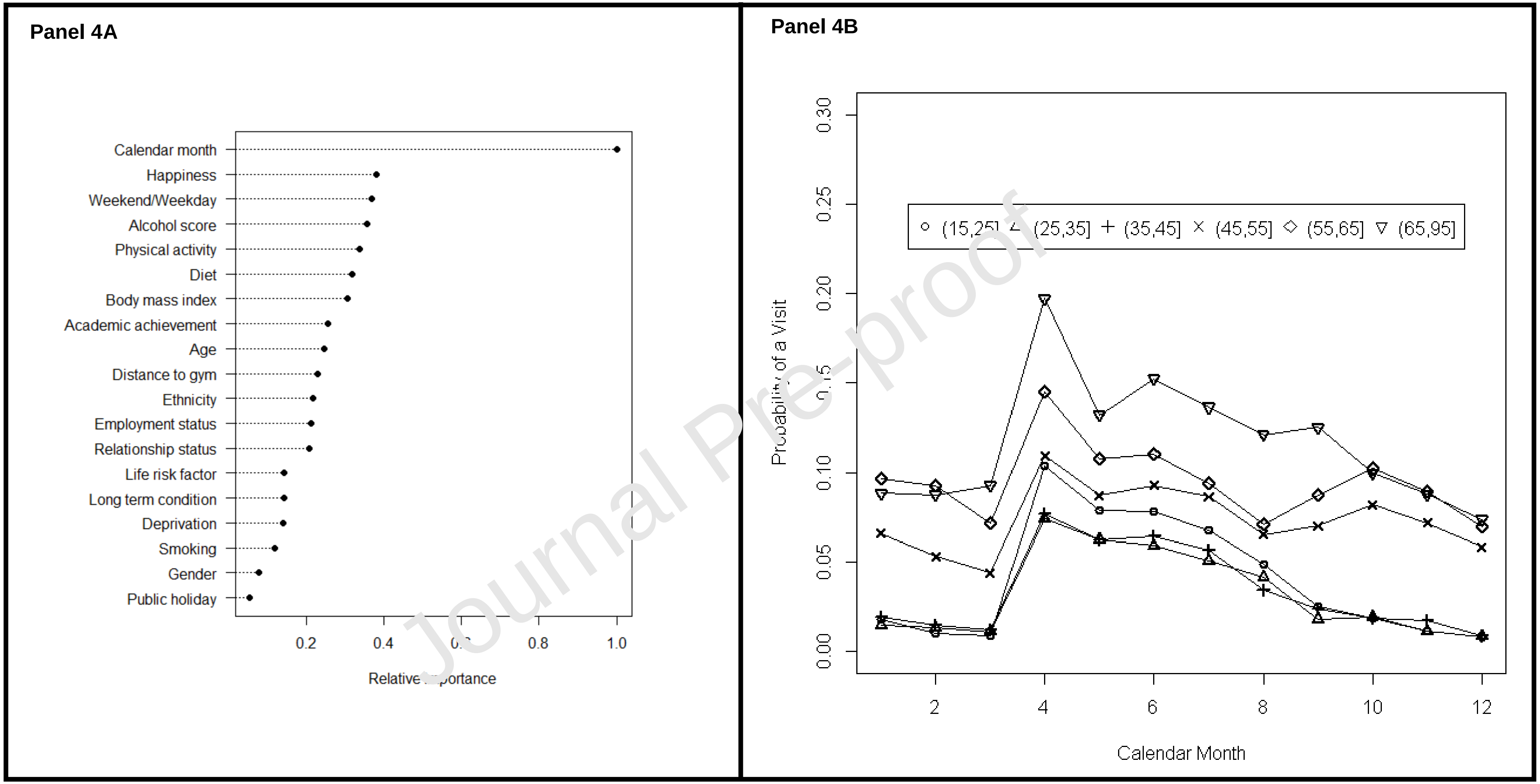

Figure 4. Panel 4A shows the relative importance of sociodemographic, lifestyle practices, and environmental variables on whether a visit was made on a particular day. Panel 4B highlights the effect of calendar month on the probability of a visit by age group.

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4. Discussion

This unique study investigated the influence of sociodemographic, lifestyle practices and environmental variables on attendance at a citywide physical activity intervention over one year. Findings show that wider determinants, such as travel distance and calendar month, were important in predicting attendance. We assessed the probability that a person will return (i.e. go more than once), the number of return visits, and visit a leisure centre on a particular day. We found that distance to a leisure centre from home was the single most influential determinant in predicting a return visit to a leisure centre. However, age was the single most important predictor in determining the number of return visits. While distance to a leisure centre was less important, the difference between the estimates for 300m and 15,000m was approximately 7–10 visits per year (i.e. 1 extra visit every 6 weeks).

Previous research has primarily focused on proximity to facilities within neighbourhoods, but seldom have data on the use of such facilities (46-48) and fewer still have this data over time. While most evidence on environmental determinants is inconsistent, our findings support previous evidence that wider determinants, such as weather or proximity to facilities, influence attendance at public health interventions (17-19, 25, 26, 28, 49). For example, a recent review demonstrated that the availability of physical activity equipment was associated with vigorous physical activity and the connectivity of trails with active commuting (25). Other evidence from 14 cities, in ten countries, on five continents, has shown that the design of urban environments has the potential to contribute substantially to physical activity (26).

Little consideration has previously been given to the effect of proximity on attendance and the possible modifying effects of demographic factors. Our study shows that proximity to a leisure centre affects whether individuals return, but only from 5km, although this effect was not evident in older men. Based on previous evidence, we can speculate that this could relate to this group's preparedness to navigate distance or established patterns of physical activity and social networking (50). Additionally, summer months were more popular than winter months. Examining the interaction between individual sociodemographic determinants, such as age or socioeconomic status, alongside wider determinants such as proximity to leisure centres will be an important direction for future research to enable a better understanding of what environmental determinants are important for specific population groups. For example, previous research has shown that favourable physical activity environments were associated with reduced obesity risk, but only among the most affluent populations (51). In contrast, this study showed few differences by socioeconomic status but showed differences in attendance by age group. Such variance in findings between studies could be due to a range of factors, including population groups studied and variation in measurement, but serve to highlight the importance of exploring the interaction between individual and environmental determinants of health.

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Levels of physical activity, happiness (52-54), social stigma (16), a lack of flexibility in opening hours (17), and irregular working hours (18, 19) have previously been highlighted as influencing adherence. However, less literature has examined associations with attendance at a public health intervention. Factors shown to be important in predicting attendance in this study included employment status and levels of physical activity. It is also important to consider other attendance determinants not captured within this study such as instructor characteristics, social support, self-efficacy and perceived behavioural control (55). Although this study does not include every possible determinant, it details participants engagement patterns within a universal, free-at-the-point-of-access, physical activity intervention. It thus has implications for both the management of people who don't attend interventions and the effectiveness of existing strategies that aim to increase attendance. Results are therefore important for both public health and physical activity providers. The findings present evidence that both environmental and sociodemographic factors drive attendance and should be considered in the future development of interventions.

This study is strengthened by the large sample from a citywide intervention, using complex models to account for the nature of the data (44). From a geospatial perspective, the inclusion of data on the use of facilities, and not just assuming that individuals use their nearest leisure centre, is a major strength (56). Finally, we examine attendance across the whole year, meaning our results are not subject to seasonal effects (12, 18). This research provides valuable routes to investigate the motives, determinants and behaviours of attendees that shape intervention delivery and design (57). Despite these strengths, this study uses self-reported data for lifestyle practices which is subject to recall bias. In addition, the results presented here may not be generalisable to other cultures and contexts and should be interpreted with this in mind. While attendance data is longitudinal, we report lifestyle practices at baseline and do not have data relating to participants' work address, which could be an equally important determinant of attendance. Moreover, this study is limited by potential changes in residential address during the study period. Our sample was primarily white British and we only have lifestyle practice data on a smaller sub-sample. It is also likely that many participants will have undertaken some physical activity outside of the recorded leisure centre visits which may limit the generalisability of the findings. However, the machine learning technique used, that includes people's baseline physical activity levels, accounted for some of this variation. In addition, session availability across intervention sites varied considerably due to opening times and differing policies.

5. Conclusions

In summary, we investigated the influence of a participant's proximity to a leisure centre, environmental determinants such as weather, and lifestyle practices on attendance at a citywide physical activity intervention over one year. This study contributes to the limited research available on associations between environmental influences and public health intervention attendance. It goes beyond much research, which rarely has data on the use of facilities over time. Triangulation between residential address, the location of a facility used over time, and levels of physical activity at baseline make this a unique contribution to evidence. Public health interventions should consider the wider determinants influencing attendance beyond lifestyle and sociodemographic characteristics. Such

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consideration also takes on added importance in the emergence of systems-based approaches to physical activity promotion.

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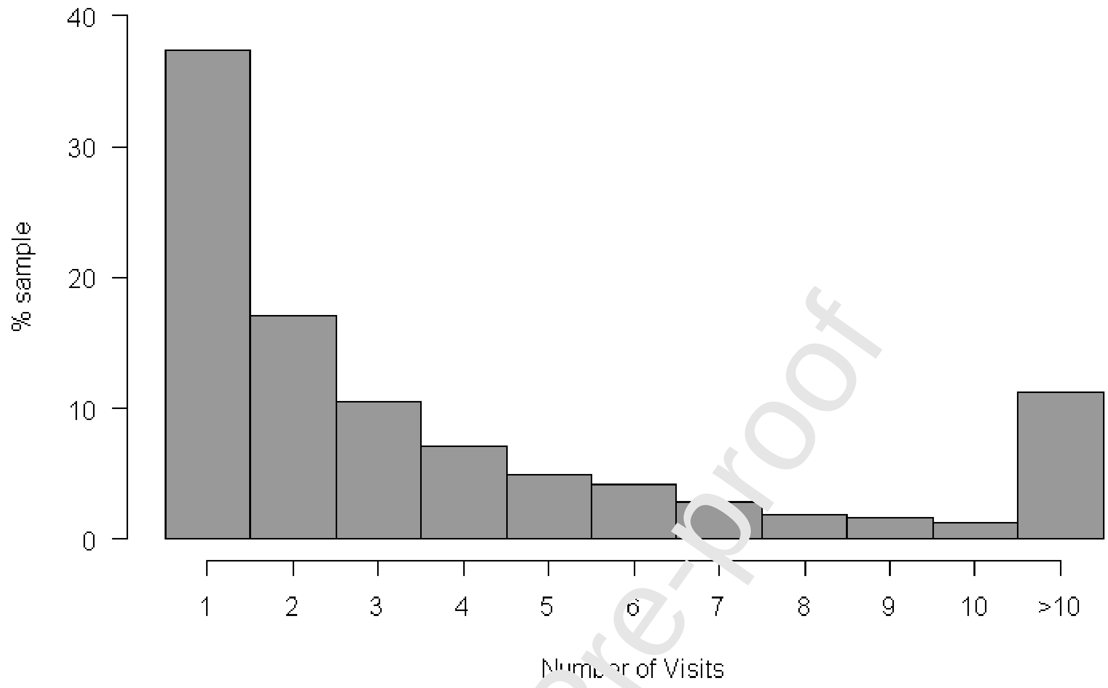

Figure S1. Distribution of the number of visits per person in the sample.

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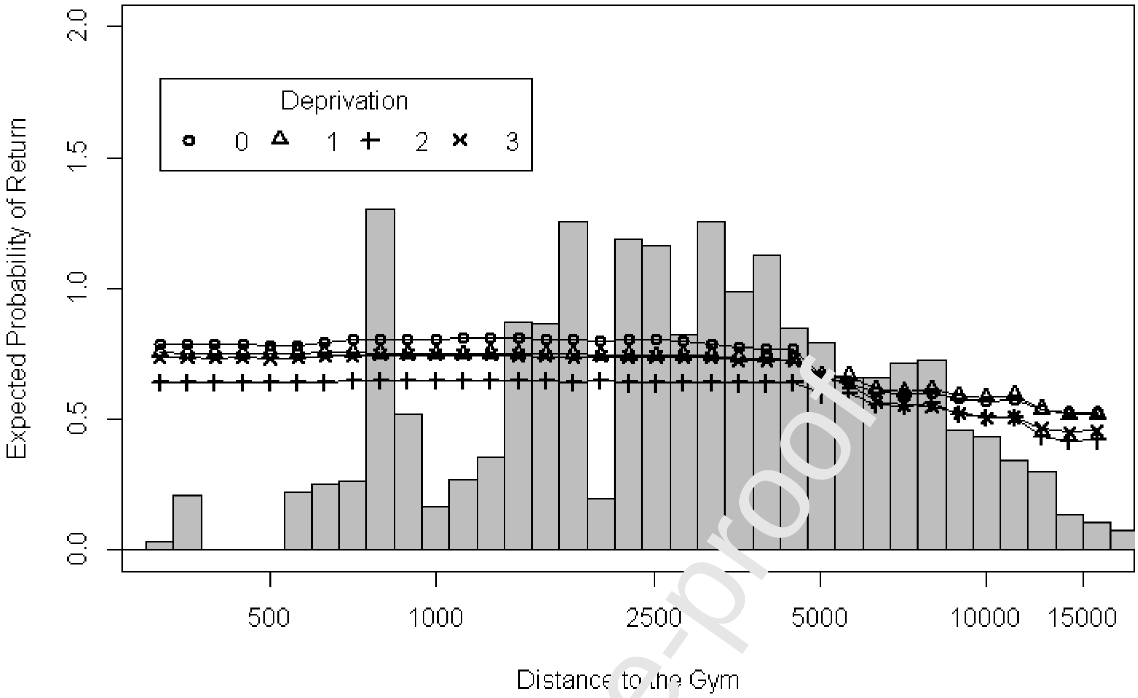

Figure S2. The expected probability of a return to the leisure centre for the observed sample conditional on the distance to the leisure centre by deprivation level (0= 3% most deprived; 1=10% most deprived; 2=20% most deprived; and 3= not deprived). The histogram in grey shows the current distribution of leisure centre distances for the sample.

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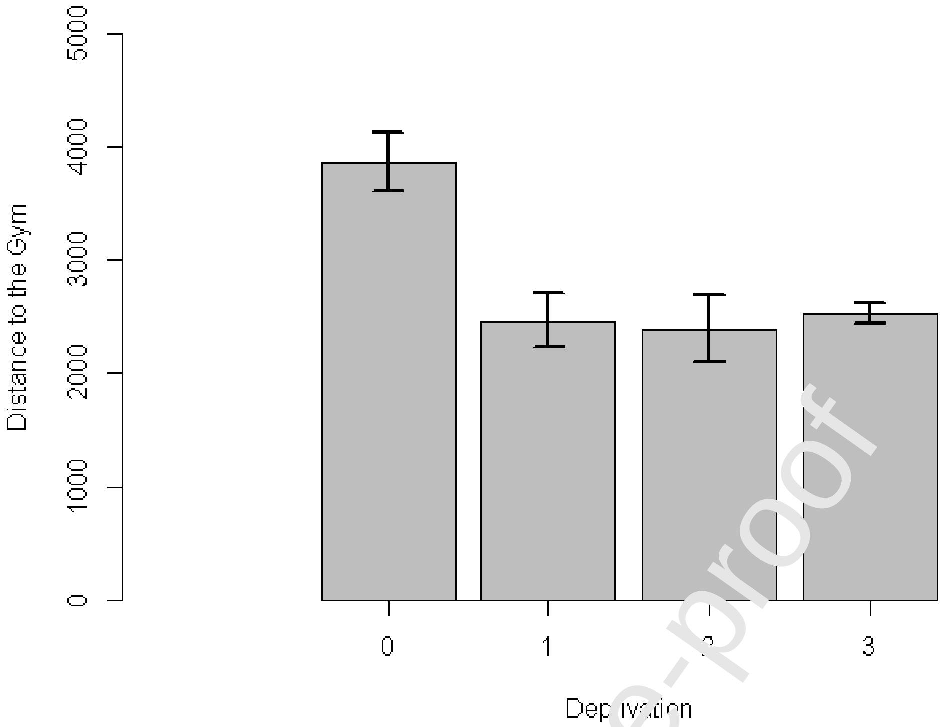

Figure S3. Distance to the leisure centre (m) by deprivation class (0= 3% most deprived; 1=10% most deprived; 2=20% most deprived; and 3= not deprived).

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Credit author statement

All authors (MH, EM, CW, AP, CG, DR and SZ) contributed substantially to this manuscript.

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Highlights

- Attendance at a city-wide public health intervention was tracked over one year.
- Individual-level determinants of attendance were important factors.
- Wider environmental determinants such as weather also influenced attendance.
- These results have significant implications for public health practice.

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