Public Health England

Protecting and improving the nation's health

Wider impacts of COVID-19 on physical activity, deconditioning and falls in older adults: technical appendix

Contents

Selection of active lives adult survey variables

Table 1 gives a summary of the demographic variables available in the Active Lives Adult Survey (ALS), those that have been included for use in the report and a summary justification.

Table 1. Selection of ALS variables

Variable	Benefits of inclusion	Included in report	Justification for exclusion
Age	Falls risk varies by significantly by age. Therefore, disaggregation contributes to model accuracy.	Yes	N/A
Sex	Falls risk varies by significantly by sex. Therefore, disaggregation contributes to model accuracy.	Yes	N/A
Ethnicity	Ethnicity is a determinant of inequality. Disaggregation is relevant for identifying and reducing health inequalities.	No	Sample size limitations would result in a binary ethnicity variable (White British vs Other). This classification would not provide enough information on ethnicity.
Index of Multiple Deprivation (IMD)	IMD is a determinant of inequality. Disaggregation is relevant for identifying and reducing health inequalities.	Partial	Descriptive statistics within the report are given by IMD quartile only but not used for modelling purposes as the sample size did not enable a breakdown by age, sex and IMD.
National Statistics Socio-economic Classification (NS-SeC)	NS-SeC is a determinant of inequality. Disaggregation is relevant for identifying and reducing health inequalities.	No	NS-SeC is a poor measure of inequality for older adults.
Region	Disaggregation of results by location is relevant to local planning.	Partial	Descriptive statistics within the report are given by region only but not used for modelling

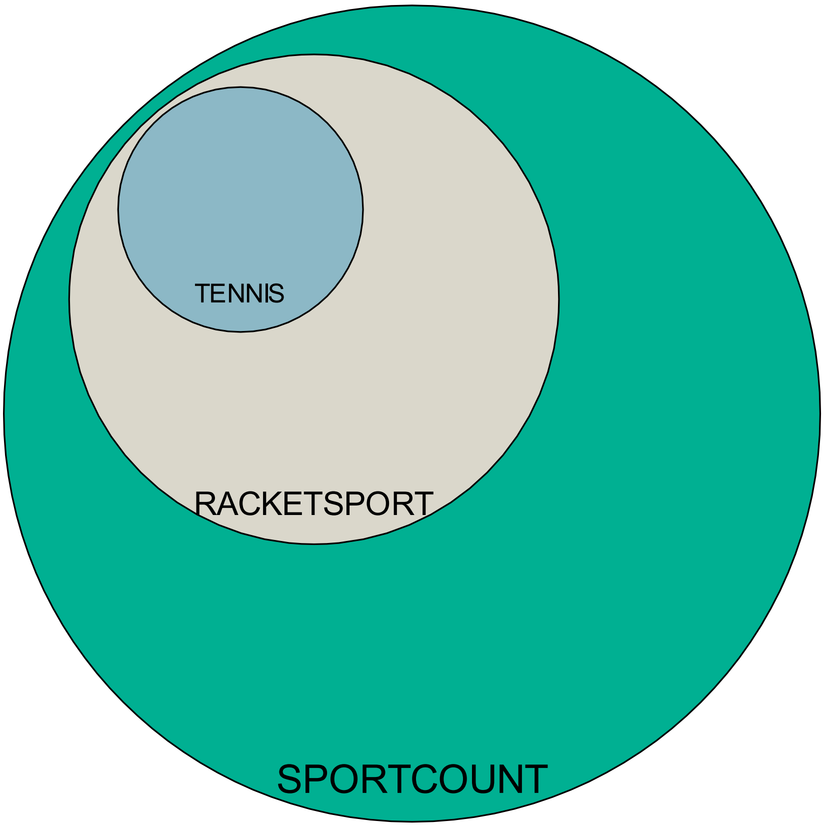
Variable	Benefits of inclusion	Included in report	Justification for exclusion
			purposes as the sample size did not enable a breakdown by age, sex and region.
Local Authority	Disaggregation of results by location is relevant to local planning.	No	Sample size for period of interest is too small to produce reliable results when including local authorities within modelling work.

Classification of ALS activities

Mutually exclusive and completely exhaustive combinations

Analysis required the classification of the number of minutes of activity performed by each individual in the ALS into strength and balance activity and all other activity. Within ALS, activity is reported for each composite, for which there are over 200 varying from broad categories (such as SportCount, which reports the duration spent of any sporting activity), to more specific categories (such as RacketSport) and individual activities (such as Tennis). There are overlaps and nesting present within each composite, Figure 1 below provides an example of this. Some specialised activities are not captured by a category or named individual activity but do contribute to the SportCount variable. These activities were not classified as strength and balance but were captured in the general physical activity calculations and were generally undertaken by individuals who participated in many different sporting activities.

Figure 1. Nested composites within ALS (not to scale)



As a result of this nesting as described above, only a selection of relevant composites were required otherwise double and even triple counting of specific activities would occur. The data dictionary for ALS contains a mapping of composites and the activities contained within them, which can be transformed into a matrix, an illustrative example of which is given in Table 2.

Table 2. Illustrative composites mapping

		Activity		
		Tennis	Badminton	Hockey
Composite	SportCount	True	True	True
	RacketSport	True	True	False
	Tennis	True	False	False
	Badminton	False	True	False
	Hockey	False	False	True

In order to avoid counting activities multiple times, we wish to select a subset of composites that counts each activity once and only once. This subset is known as a mutually exclusive and completely exhaustive (MECE) combination.

Whilst in the example given in Table 2, it should be clear that just using SportCount is a valid MECE combination, this will not be informative for our modelling as SportCount contains both strength and balance activities and all other activities. Composites that contain such a mixture of activities will be classified as vague and removed before the selection of the MECE combination occurs. Remaining composites will be classified as precise, with Table 3 displaying our illustrative example after this filtering.

Table 3. Illustrative precise composites mapping

		Activity		
		Tennis	Badminton	Hockey
Composite	RacketSport	True	True	False
	Tennis	True	False	False
	Badminton	False	True	False
	Hockey	False	False	True

We then identify our MECE combination by first abstracting the precise mapping into a binary matrix, as illustrated in (2), before performing row reduction to remove linearly dependent rows.

$$\begin{pmatrix} 1 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{1}$$

During this row reduction, we prioritise removing rows that represent larger composites over their smaller sub-composites. For example, in (1), the first 3 rows are linearly dependent. Here, we can either remove the first (representing RacketSport), or both the second and third (representing Tennis and Badminton). Our approach prioritising removing the first row (RacketSport), as keeping the smaller sub-composites (Tennis and Badminton) allow the MECE combination chosen to be as nuanced as possible. The result of row reduction using this prioritisation on our illustrative example is given in (2).

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \tag{2}$$

These leads to the chosen MECE combination of composites being Tennis, Badminton and Hockey as this list captures each activity once and only once (thus meeting the definition of a MECE combination).

If Badminton was not available as a composite, as in Table 4, our chosen MECE combination would be RacketSport and Hockey. This remove the Tennis composite as, including that for this example would result in the combination either double counting the tennis activity (if both RacketSport and Tennis were included) or missing the badminton activity (if RacketSport were excluded).

Table 4. Complex illustrative composites mapping

		Activity		
		Tennis	Badminton	Hockey
Composite	SportCount	True	True	True
	RacketSport	True	True	False
	Tennis	True	False	False
	Hockey	False	False	True

After a MECE combination has been identified, an elementary verification was undertaken to ensure that categorisations of activities within ALS using this combination had not led to any unintended data duplication. This was done by comparing to the MEMS7_ALL value within ALS which gave an estimate of total activity performed.

The composite HillWalk was neither a subset of another composite nor a linear combination of other composites but led to some double counting when included. It was therefore decided to remove this composite before analysis.

Strength and balance classification list

There were 81 activities without an equivalent in Strain and others which were categorised by the advisory group. In total, 71 composite activities were classed as strength and balance and 11 were not. The full classification of these activities is given in Table 5.

Table 5. Classification of activities

Activity label	Strength and balance
Abseiling	Yes
Angling	No
Archery	Yes
Baseball or softball	Yes
Basketball	Yes
Body weight exercises	Yes
Bowls or boules	Yes
Boxing	Yes
Canoeing	Yes
Cardio class	Yes
Caving or pot holing	Yes
Climbing or bouldering	Yes
Core strength class	Yes
Cricket	Yes
Croquet	No
Cross training machine	Yes
Cycling	Yes
Dance	Yes
Darts	No
Dodgeball	Yes
Equestrian	Yes
Fell running	Yes
Fencing	Yes
Football	Yes
Frisbee or ultimate frisbee	Yes
Gardening	No
Gliding paragliding or hand gliding	Yes
Goalball	Yes
Golf	Yes
Gym session	Yes
Gymnastics, trampolining or cheerleading	Yes
Handball	Yes
High ropes	Yes
Hockey	Yes
Hula hooping	Yes
Ice hockey	Yes
Interval sessions	Yes
Judo	Yes
Lacrosse	Yes
Martial arts	Yes

Activity label	Strength and balance
Modern pentathlon	Yes
Motor sports	No
Mountaineering and scrambling	Yes
Netball	Yes
Obstacle course (for example, Tough Mudder)	Yes
Orienteering	Yes
Other exercise machine	Yes
Other fitness or exercise class	Yes
Parkour or free running	Yes
Pilates	Yes
Pool	No
Racket sports	Yes
Roller or skating sports	No
Rounders	Yes
Rowing	Yes
Rugby league	Yes
Rugby union	Yes
Running	Yes
Sailing	Yes
Scuba diving or snorkelling	No
Shooting	Yes
Skipping	Yes
Skittles	Yes
Sledding luge tobogganing	No
Snooker	No
Snowsport	Yes
Step machine	Yes
Surfing, board surfing, body boarding, kite surfing	Yes
Swimming diving or water polo	Yes
Taekwondo	Yes
Tai chi	Yes
Ten-pin bowling	Yes
Track and field athletics	Yes
Triathlon	Yes
Volleyball	Yes
Walking	No
Water-skiing	Yes
Weights session	Yes
Wheelchair basketball	Yes
Wheelchair rugby	Yes
Wrestling	Yes

Activity label	Strength and balance
Yoga	Yes

Validation of data

Baseline fallers data

Data on the numbers of fallers extracted from the Projecting Older People Population Information (POPPI) system is a modelled estimate as this is based on data from the 2005 Health Survey for England combined with ONS modelled population projections for 2020. Validation work has compared this data with data extracted from the English Longitudinal Study of Ageing (ELSA) [1], and shows that these estimates are comparable (see Table 6 and

Table ***7***).

Table 6. POPPI/HSE falls prevalence data [2]

Age	Prevalence (%) – male	Prevalence (%) – female
65 to 69	18	23
70 to 74	20	27
75 to 79	19	27
80 to 84	31	34
85 and over	43	43

Table 7. ELSA falls prevalence data

Age	Prevalence (%) – male	Prevalence (%) – female
60 to 69	20.8	26.6
70 to 79	27.7	30.5
80 and over	33.2	35.1

Falls per faller

Within the main study, we estimated the baseline number of falls per faller within a given 12-month period for older adults to be approximately 1.77. This was calculated using the rate of falls per person-years and the rate of fallers per person-years in the control group across all studies included within Sherrington and others [3].

These values can also be extracted from the 2005 Health Survey for England and are presented in Table 8 for comparison.

Table 8. Rates of falls and fallers

Source	Rate of fallers	Rate of falls	Average falls per faller
HSE 2005	0.26	0.76	2.90
Sherrington and others [3]	0.48	0.85	1.77

There would be benefits to using the values from HSE 2005, such as consistency with the baseline prevalence of fallers we are using and the ability to extract different average falls per faller for each age group and sex. However, the standard error for the rate of falls is considerable, even without aggregation, due to the relevant sample size, leading to a 95% confidence interval for the rate in all individuals aged 65 and over of [0.57, 0.95], which would correspond to an average falls per faller of between 2.19 and 3.65.

Due to this level of uncertainty, it was decided to use the equivalent values from Sherrington and others [3] as, at worst, this would lead to understating the impact of deconditioning on the number of falls and the associated costs by approximately one-third.

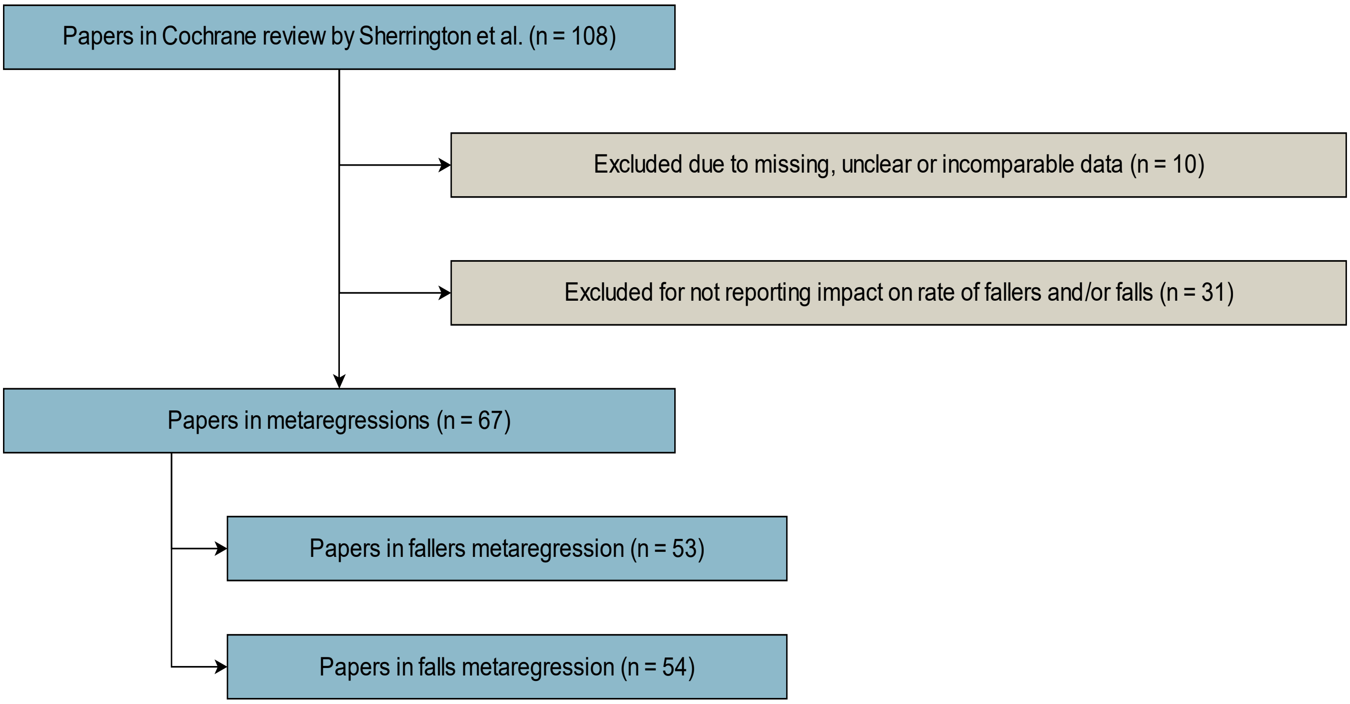
Impact of activity levels on fallers and falls

In order to link changes in physical activity levels to changes in the number of fallers and falls, we must first quantify the impact that a change has on the rates of fallers and falls. This will be done through meta-regressions on the results of studies that record the rate of falls and/or fallers within a control group and a comparator group undertaking an intervention consisting of additional weekly physical activity.

Selection of studies to include

Of the 108 studies included in the Cochrane review by Sherrington and others [3], 41 were excluded from the meta-regression. 31 of these exclusions were due to the results of the study not including the impact of the intervention on the rate of falls and/or fallers. A further 10 were excluded due to necessary data being missing or unclear, or incomparable control interventions that prevented the rate ratios being linked to an increase in physical activity. Of the 67 remaining studies used within the meta-regressions, 13 solely reported the impact on the rate of fallers, 14 on the rate of falls, whilst 40 reported on both rates. This information is summarised in Figure *2*.

Figure 2. Selection of studies for meta-regression



Identification and imputation of adherence

The adherence of participants in a study to the intervention will impact any changes measures compared to the control group and thus should be accounted for within our meta-regressions. For the 67 studies identified for inclusion, an intervention adherence value could be extracted or estimated for 48 of these. Where an average intervention attendance or adherence was given explicitly, this was extracted directly from the paper. Where this value was not explicitly given, an estimate was calculated using a weighted average – for example, if 70% of participants completed 60% or more of the intervention programme, we would estimate an adherence of 65% as calculated in (3).

$$Adherence = \left(\frac{(1+0.6)}{2} * 0.7\right) + \left(\frac{0.6}{2} * (1-0.7)\right) = 0.65 \tag{3}$$

Example calculation for adherence: If a study reports that 70% of participants completed 60% or more of an intervention program, we calculate a weighted average for the adherence. We weight the midpoints either side of the 60% value (0.8 and 0.3) by the proportions of individuals who completed (0.7) and didn't complete (0.3) at least 60% of the program. This gives an estimated adherence of 65%.

For the remaining 19 studies where adherence was not reported and could not be estimated from values given, the value was imputed based on reported rate ratios, the length of the intervention in weeks and the duration of the intervention in minutes per week. This imputation was performed using the predictive mean matching methodology within the mice package in R.

Meta-regression model

For both meta-regressions, a multiplicative model was chosen linking the rate ratio to the duration of the intervention in minutes per week and the intervention adherence. This model was chosen as it allows us to ensure that an intervention with zero adherence or zero length has no impact on the rate of fallers and/or fallers. The use of adherence as a scaling factor was included as an activity with a duration of 60 minutes per week with an adherence of 50% was assumed to be equally effective at a population level when compared with an activity of 30 minutes per week with complete adherence. The final formula chosen for the meta-regression therefore was as in (4).

$$(RateRatio - 1) = \alpha * Duration * Adherence \tag{4}$$

Meta-regression equation: Rate ratio minus one is equal to a scaling term multiplied by the programme duration and adherence. An estimated value for this scaling term is produced by the meta-regression.

Using the metafor package in R we get the estimates for α for the 2 meta-regressions as given in

Table 9.

Table 9. Meta-regression results

Value	Estimate (95% Confidence Interval)	Standard error	p-value
Fallers	-0.0014 (-0.0021, -0.0007)	0.0003	0.0002
Falls	-0.0020 (-0.0028, -0.0013)	0.0004	<0.0001

The results of these meta-regressions are displayed as bubble plots in Figure 3 and Figure 4.

For clarity, the axes on these figures have been truncated to focus on the region with the greatest number of results. As such, a small number of studies that were included within the meta-regressions are not plotted in these figures as they contain values outside of this range.

Figure 3. Bubble plot for fallers meta-regression

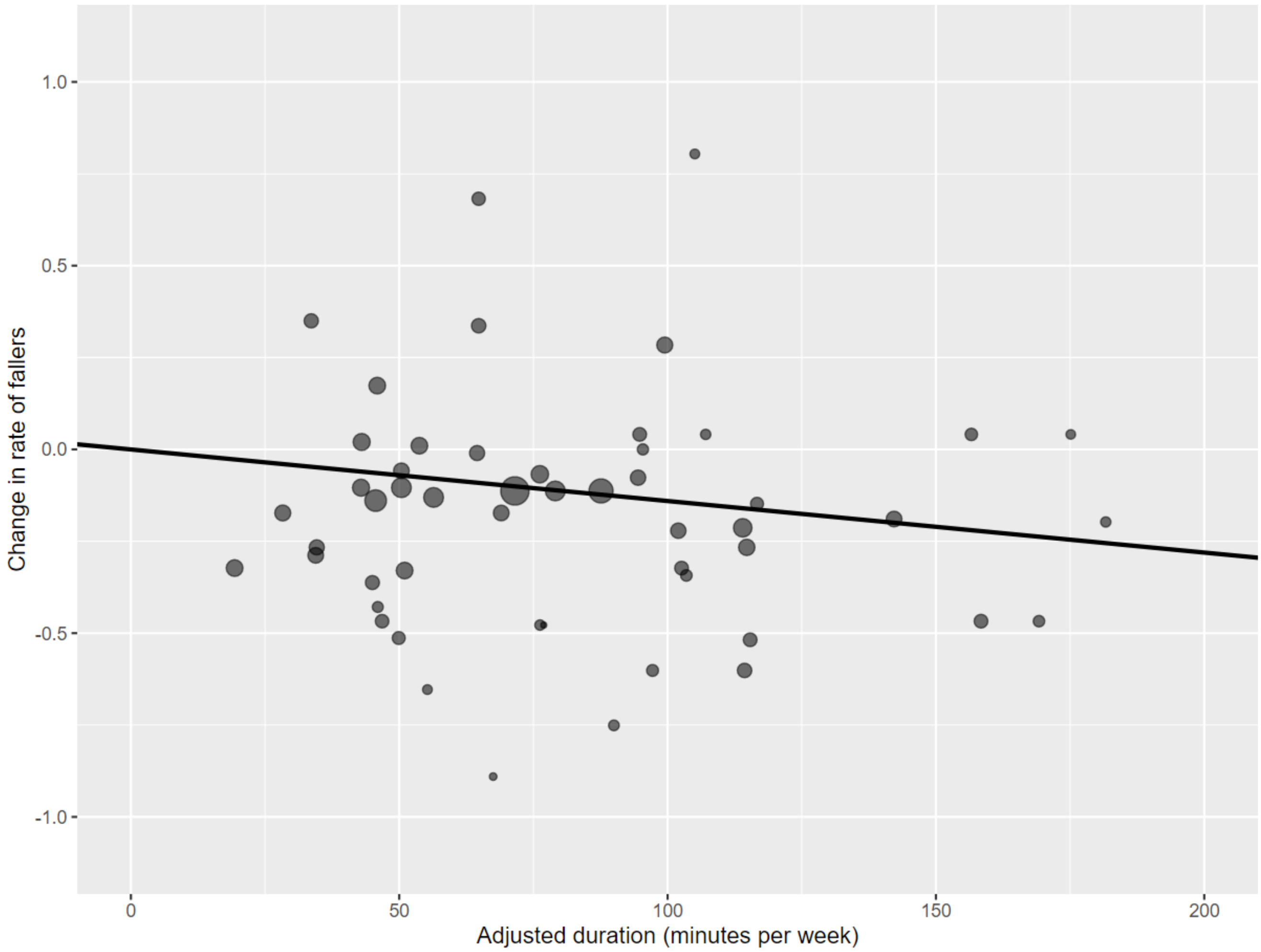
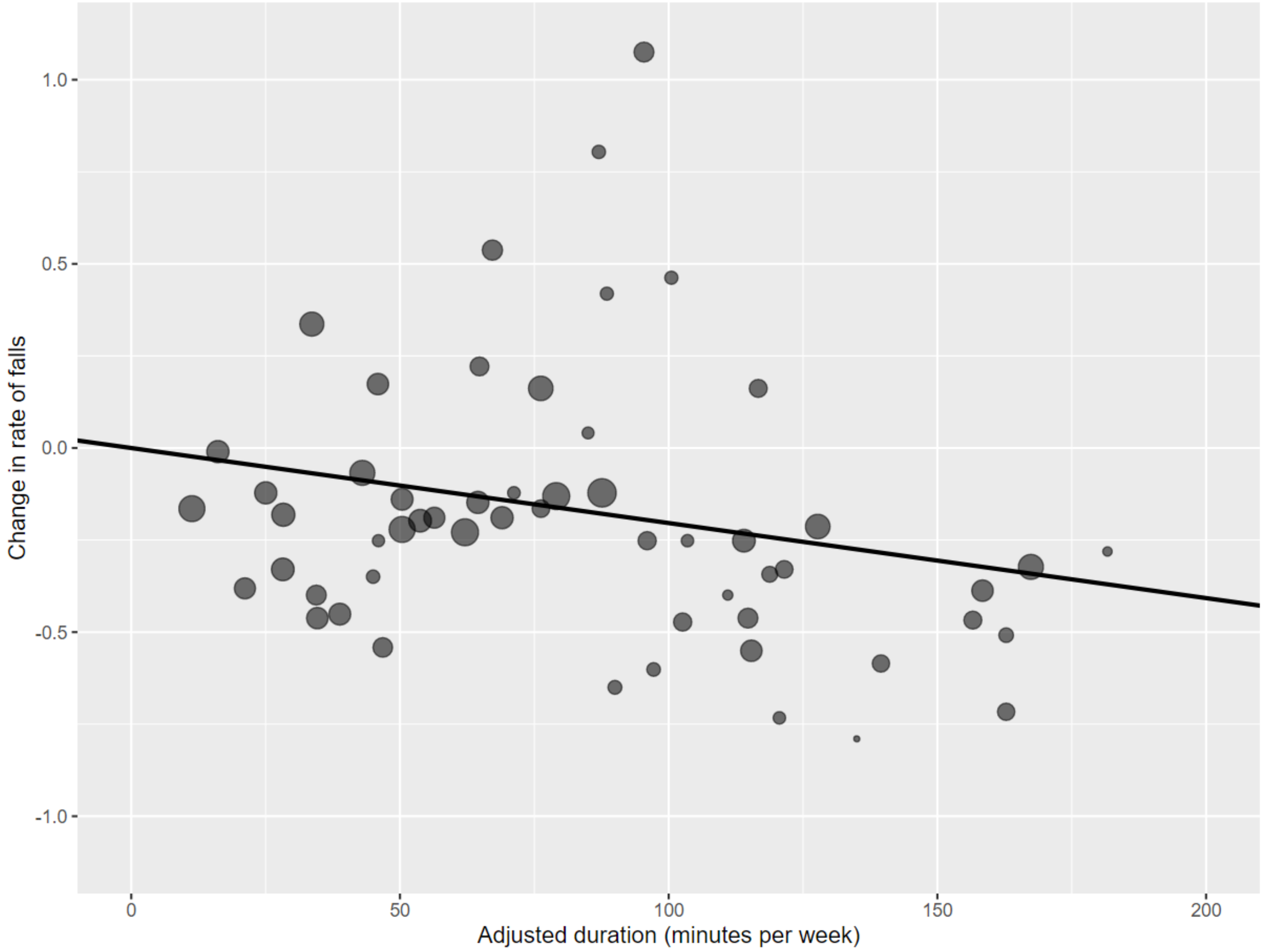


Figure 4. Bubble plot for falls meta-regression



Assuming that the data recorded in ALS is accurate and the data represents 100% adherence, the results from the meta-regression show that one additional minute of activity per week reduces the rate of fallers by 0.14% and the rate of falls by 0.20%. Scaling these values and calculating the average falls per faller as the ratio between the rate of falls and the rate of fallers, we obtain the impacts given in Table 10.

Table 10. Scaled meta-regression results

Value	Impact of additional activity per week			
	1 minute	30 minutes	1 hour	2 hours
Falls rate	-0.20%	-5.94%	-11.53%	-21.73%
Fallers rate	-0.14%	-4.12%	-8.08%	-15.50%
Average falls per faller	-0.06%	-1.90%	-3.75%	-7.37%

Number of fallers by activity level

To estimate the number of fallers by activity level, we combine the results of the meta-regression, baseline number of fallers and falls and the baseline activity.

We first calculate $RR_{fallers}(t, A, S)$, the calibrated risk of being a faller for a given level of activity, by age group and sex as given in (5). Here, $p_{act}(t, A, S, Y)$ the proportion of individuals within a given age group and sex who undertake t minutes of activity per week under a given scenario year[1]. This is taken from the activity levels data extracted from ALS and should sum to 1 for any given age group and sex combination. $I_{fallers}$ represents the impact of 1 additional minute of activity on the rate of fallers identified through the meta-regression (that is, -0.0014).

$$RR_{fallers}(t, A, S) = \frac{\left(1 + I_{fallers}\right)^t}{\int p_{act}(t, A, S, 2019) * \left(1 + I_{fallers}\right)^t \, dt} \qquad (5)$$

Calibrated risk equation: For each age group and sex, the calibrated risk of being a faller for a certain amount of activity is equal to the impact of that amount of activity on the rate of fallers divided by the mean impact in 2019

We then use this to calculate $M_{fallers}(t, A, S)$, the expected number of fallers within a specific age group and sex combination if we assumed that all individuals performed the same amount of activity per week, as in (6). Here, we multiply the relative risk as calculated in (5) by $n_{fallers}(A, S, 2019)$, the total number of fallers within a given age group and sex. This value is extracted from POPPI as the baseline estimate for the number of fallers.

$$M_{fallers}(t, A, S) = RR_{fallers}(t, A, S) * n_{fallers}(A, S, 2019) \qquad (6)$$

Baseline fallers equation: For each age group and sex, the baseline number of fallers for a certain amount of activity is equal to the calibrated risk for that level of activity multiplied by the total number of fallers in 2019

To calculate $n_{fallers}(t, A, S, Y)$, the actual number of fallers in a given scenario year, for a specified activity level, age group and sex, we perform (7). This multiplies the expected number of fallers for that activity level as calculated in (6) by the appropriate proportion.

[1] For ease of presentation, the calculations in this section are given as though t is continuous. However, in the modelling the amount of activity undertaken per week was grouping into discrete 30 minutes activity bands (for example, 0 to 30 minutes, 30 to 60 minutes, and so on.) with the calculations in this section using t as the mid-point of each group (for example, 15 minutes, 45 minutes, and so on) and summing appropriately (rather than taking integrals).

$$n_{fallers}(t, A, S, Y) = M_{fallers}(t, A, S) * p_{act}(t, A, S, Y) \quad (7)$$

Number of fallers equation: For each age group and sex, the number of fallers for a certain amount of activity is equal to the baseline fallers for that level of activity multiplied by the proportion of the population undertaking that level of activity in a given year

To calculate $n_{fallers}(A, S, Y)$, the total number of fallers for a specified scenario year and a given age group and sex, we can summarise (7) across all possible activity levels as in (8). It should be clear that for the baseline scenario, this is equal to $n_{fallers}(A, S, 2019)$ as expected.

$$n_{fallers}(A, S, Y) = \int n_{fallers}(t, A, S, Y)\, dt \quad (8)$$

Total number of fallers equation: For each age group and sex, the total number of fallers is the integral across the amount of activity undertaken of the number of fallers for each level of activity in a given year

Similar calculations can be performed to report the number of falls over any combination of variables by summarising over those to be removed.

Number of falls by activity level

To estimate the number of falls by activity level, we perform a similar methodology as for the number of fallers above. We assume here that the number of falls is impacted by the level of activity.

We begin by identifying the proportion of fallers who undertake t minutes of activity per week in a scenario year $p_{fallers}(t, Y)$, given in (9), and use this to calculate $RR_{average}(t)$, the calibrated risk for the average number of falls for a faller for a given level of activity as given in (10). Here, $I_{average}$ represents the impact of 1 additional minute of activity on the average falls per faller identified through the meta-regression (that is, -0.0006).

$$p_{fallers}(t, Y) = \frac{n_{fallers}(t, Y)}{n_{fallers}(Y)} \quad (9)$$

Proportion of fallers equation: The proportion of fallers for a certain amount of activity is equal to the number of fallers undertaking that amount of activity divided by the total number of fallers across all levels of activity in a given year

$$RR_{average}(t) = \frac{\left(1 + I_{average}\right)^t}{\int p_{fallers}(t, 2019) * \left(1 + I_{average}\right)^t dt} \tag{10}$$

Calibrated risk equation: For each age group and sex, the calibrated risk for average falls per faller for a certain amount of activity is equal to the impact of that amount of activity on the rate of falls per faller divided by the mean impact in 2019

We can then calculate $n_{falls}(t, A, S, Y)$, the number of falls in a given scenario year for a specified activity level, age group and sex as in (11), where $n_{average}$ is the average number of falls per faller in the baseline scenario identified above (that is, 1.77).

$$n_{falls}(t, A, S, Y) = RR_{average}(t) * n_{fallers}(t, A, G, R, Y) * n_{average} \tag{11}$$

Number of falls equation: For each age group and sex, the number of falls for a certain amount of activity in a year is equal to the calibrated risk for that level of activity multiplied by the number of fallers for that level of activity multiplied by the average number of falls be faller in the baseline scenario

Summarising this over variables in the baseline scenario year and dividing by $n_{fallers}(2019)$, the total fallers in the baseline scenario year, this equals $n_{average}$ as is expected.

Estimating the values under a scenario

In the above calculations, Y refers to the scenario of interest, such as baseline (2019) or coronavirus (COVID-19) (2020).

In certain calculations, such as (5) or (6), where we are calculating a relative risk or a similar time-invariant value, we use the extracted baseline data as this is the only scenario for which values for all required variables can be identified using published data.

When performing calculations that apply to a specific scenario, such in (7) and (11), we combine these time-invariant values with the activity levels observed in ALS data for the given scenario. This allows us to estimate values, such as the number of fallers and falls under this scenario, for which no data presently exists.

We can also use this process to model the impacts of an intervention. By appropriately modifying the existing data to reflect assumed impacts under an intervention scenario, we can use the methodology presented to model the changes to the numbers of fallers and falls that occur as a result of the given intervention. For example, if we wished to model an intervention under which older adults increase their physical activity levels by 10% relative to the amount performed during the pandemic, we would scale the activity levels observed during the pandemic by 10%, before proceeding as outlined above.

Care pathway costs

In Table 11 and Table 12 taken from the PHE Falls Prevention ROI Tool [4] and inflated using GDP deflators [5], we present the health and social care costs used within the modelling work.

Table 10 presents the primary healthcare unit costs used within the model as per person-event. For example, the 2019 to 2020 [2] unit cost for an individual visiting a GP is £39.35. Table 11 presents the secondary health and social care costs used within the model. For care home, this is split into nursing and residential care and adjusted for the average amount of care that is self-funded, with costs being given per person-week. For example, the 2019 to 2020 average cost for a individual staying in a NHS care home is £524 per week. In this table, we also give the value for a care package at usual residence. This is a unit cost and is given per person-event.

Table 11. Healthcare costs related to falls

Parameter	Unit cost (2015 to 2016)	Unit cost (2019 to 2020)
GP visit	£36.00	£39.28
A&E visit requiring admission	£100.53	£109.70
A&E visit requiring no admission	£90.29	£98.51
Ambulance call-out to hospital	£236.00	£257.50
Non-hip fracture – hospital inpatient stay	£7,949.00	£8,673.00
Hip fracture – hospital inpatient stay	£8,955.49	£9,771.00
Hip fracture – 1st year follow-up costs	£527.34	£575.40
Hip fracture – 2nd year costs	£2,211.73	£2,332.00
Geriatric long-stay	£14,659.28	£15,994.00

Table 12. Secondary health and social care costs related to falls

<table>
<tr><th colspan="2">Resource</th><th>Weekly cost (2015 to 2016)</th><th>Weekly cost (2019 to 2020)</th><th>% self-funded</th><th>System cost (2019 to 2020)</th></tr>
<tr><td rowspan="2">NHS Care Home</td><td>Nursing Care</td><td>£113</td><td>£123</td><td>0%</td><td rowspan="2">£524/week</td></tr>
<tr><td>Residential Care</td><td>£550</td><td>£600</td><td>33%</td></tr>
<tr><td rowspan="2">Local Authority Care Home</td><td>Nursing Care</td><td>£0</td><td>£0</td><td>0%</td><td rowspan="2">£406/week</td></tr>
<tr><td>Residential Care</td><td>£555</td><td>£606</td><td>33%</td></tr>
</table>

[2] Financial year.

<table>
<tr><th colspan="2">Resource</th><th>Weekly cost (2015 to 2016)</th><th>Weekly cost (2019 to 2020)</th><th>% self-funded</th><th>System cost (2019 to 2020)</th></tr>
<tr><td rowspan="2">Private Care Home</td><td>Nursing Care</td><td>£113</td><td>£123</td><td>100%</td><td rowspan="2">£0/week</td></tr>
<tr><td>Residential Care</td><td>£550</td><td>£600</td><td>100%</td></tr>
<tr><td colspan="2">Care Package at Usual Residence</td><td colspan="3">N/A</td><td>£2,080</td></tr>
</table>

The values can be combined with the probabilities of each care pathway identified in the PHE Falls Prevention ROI Tool [4] to calculate the average system costs (scaled to 2019/20 values) per fall. These values, their total and how much each pathway contributes to the average total cost of a fall are given in Table 13. Please note that values are rounded so may not sum correctly.

Table 13. Average cost of a single fall

Pathway	Prop. of falls (%)	Avg. cost (£/fall)	Prop. of total cost (%)
GP visit	10.20	4.01	0.48
Ambulance call-out	12.20	31.42	3.78
A&E visit (no admission)	10.40	10.25	1.23
A&E visit (admission)	5.60	6.14	0.74
Inpatient stay (no fracture)	3.86	335.12	40.32
Inpatient stay (fracture)[3]	1.74	220.10	26.48
Geriatric long-stay ward	0.32	50.96	6.13
NHS care home	0.08	54.15	6.52
LA care home	0.03	16.10	1.94
Home care package	4.95	102.90	12.38
Total		**831.14**	

[3] Including 1st and 2nd year follow up costs.

Expanded results

Detailed scenario costs

A summary of the number of fallers and falls, and the associated system costs for the baseline, COVID-19 and intervention scenarios are given in Table 14, Table 15 and Table 16, respectively. Please note that due to rounding, summary rows and columns may not appear to sum correctly.

Table 14. Expanded results – baseline scenario

Age	Sex	Fallers (000s)	Falls (000s)	Costs (£ million)			
				Health	Social (NHS)	Social (LAs)	Total
65 to 69	Male	243	423	279	5	68	352
70 to 74	Male	269	470	309	6	75	390
75 to 79	Male	178	314	207	4	50	261
80 to 84	Male	200	354	233	5	57	295
85 and over	Male	229	410	270	5	66	341
65 and over	Male	1,120	1,972	1,297	25	316	1,639
65 to 69	Female	331	581	383	7	93	483
70 to 74	Female	398	699	460	9	112	581
75 to79	Female	291	517	340	7	83	430
80 to 84	Female	277	495	326	6	79	411
85 and over	Female	381	690	454	9	111	573
65 and over	Female	1,677	2,982	1,962	38	478	2,478
65 to 69	All	575	1,004	661	13	161	834
70 to 74	All	667	1,169	769	15	187	971
75 to79	All	470	831	547	11	133	691
80-84	All	477	849	559	11	136	706
85 and over	All	609	1,100	724	14	176	914
65 and over	All	2,797	4,953	3,259	63	794	4,117

Table 15. Expanded results – COVID-19 scenario

Age	Sex	Fallers (000s)	Falls (000s)	Costs (£ million)			
				Health	Social (NHS)	Social (LAs)	Total
65 to 69	Male	260	460	303	6	74	383
70 to 74	Male	289	513	338	7	82	427
75 to 79	Male	187	333	219	4	53	277
80 to 84	Male	207	371	244	5	60	308
85 and over	Male	231	418	275	5	67	347
65 and over	Male	1,175	2,096	1,379	27	336	1,742

Age	Sex	Fallers (000s)	Falls (000s)	Costs (£ million)			
				Health	Social (NHS)	Social (LAs)	Total
65 to 69	Female	345	613	403	8	98	509
70 to 74	Female	422	754	496	10	121	627
75 to 79	Female	300	537	354	7	86	447
80 to 84	Female	284	514	338	7	82	427
85 and over	Female	382	694	456	9	111	577
65 and over	Female	1,733	3,112	2,048	40	499	2,586
65 to 69	All	605	1,073	707	14	172	893
70 to 74	All	711	1,268	835	16	204	1,055
75 to 79	All	486	871	573	11	140	724
80 to 84	All	491	885	582	11	142	735
85 and over	All	614	1,111	731	14	178	924
65 and over	All	2,907	5,207	3,426	66	835	4,328

Table 16. Expanded results – intervention scenario

Age	Sex	Fallers (000s)	Falls (000s)	Costs (£ million)			
				Health	Social (NHS)	Social (LAs)	Total
65 to 69	Male	259	457	301	6	73	381
70 to 74	Male	287	510	336	7	82	425
75 to 79	Male	186	332	219	4	53	276
80 to 84	Male	207	370	244	5	59	308
85 and over	Male	231	417	275	5	67	347
65 and over	Male	1,170	2,086	1,375	27	335	1,737
65 to 69	Female	344	609	402	8	98	507
70 to 74	Female	420	751	495	10	121	626
75 to 79	Female	299	536	353	7	86	446
80 to 84	Female	284	513	338	7	82	427
85 and over	Female	382	693	457	9	111	577
65 and over	Female	1,728	3,102	2,045	40	498	2,583
65 to 69	All	602	1,067	703	14	171	888
70 to 74	All	708	1,262	832	16	203	1,050
75 to 79	All	485	868	572	11	139	722
80 to 84	All	490	883	582	11	142	735
85 and over	All	613	1,110	732	14	178	924
65 and over	All	2,898	5,189	3,420	66	834	4,320

Scenario costs by resource

A breakdown of the costs for each scenario across the entire older adult population into individual resources is given in Table 17. Please note that values are rounded so may not sum correctly.

Table 17. Costs by resource and scenario

Resource type	Resource	Costs per scenario (£ million)		
		Baseline	COVID-19	Intervention
Health	GP visit	198	209	208
	Ambulance call-out	156	164	163
	A&E visit (no admission)	51	53	53
	A&E visit (admission)	30	32	32
	Inpatient stay (no fracture)	1,660	1,745	1,739
	Inpatient stay (fracture)[4]	1,090	1,146	1,142
	Geriatric long-stay ward	252	265	264
Social (NHS)	NHS care home (nursing costs)	63	66	66
Social (LAs)	NHS care home (residential costs)	205	216	215
	LA care home (residential costs)	80	84	84
	Home care package	510	536	534

[4] Including 1st and 2nd year follow up costs.

Validation of modelled costs

A commonly cited overall cost of falls in older adults is £2.3 billion, appearing in NICE clinical guidance (CG161) [6]. This guidance was published in 2013, with cost estimates taken from literature published in 2011, so is likely to be a significant underestimation for present costs. The approach used to calculate this value is also unclear and whether this value relates to the total cost of falls in older adults to the NHS, to the total cost of falls in older adults to the health and social care system or the total system cost related to severe falls in older adults that result in fractures [6 to 10] .

Whilst the uncertainties surrounding this cost required us to model the baseline cost of falls in older adults using a different methodology, this figure is useful as a form of validation. To ensure that the £2.3 billion cost from the NICE clinical guidance and the baseline costs produced by our modelling work were as comparable as possible, the £2.3 billion figure was upshifted to take into account inflation and population changes. Assuming this figure represents the costs in 2011, we can use GDP data to identify that this figure must be increased by appropriately 22% to account for inflation changes [5]. Using ONS population data over the same period, we see a growth in the numbers of individuals aged 65 and over in England of over 20%, rising from an estimated 8,729,667 in 2011 to a projected 10,505,333 today [11]. Scaling the £2.3 billion estimate for the cost of falls in 2011, we get an equivalent cost of approximately £3.4 billion today.

Within the main report, we estimate that under the baseline scenario the total cost of falls in older adults to the NHS and social care system is approximately £4.12 billion per year. Of this, £3.27 billion is incurred as direct healthcare costs, £63 million as social care costs to the NHS and £796 million as social care costs to local authorities.

While we cannot directly compare the upscaled cost to £3.4 billion to any of these values due to the uncertainties in the scope, we believe there is enough similarity to provide a level of validation for the results of our methodology.

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Public Health England exists to protect and improve the nation's health and wellbeing, and reduce health inequalities. We do this through world-leading science, research, knowledge and intelligence, advocacy, partnerships and the delivery of specialist public health services. We are an executive agency of the Department of Health and Social Care, and a distinct delivery organisation with operational autonomy. We provide government, local government, the NHS, Parliament, industry and the public with evidence-based professional, scientific and delivery expertise and support.

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