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SO17859 Research into valuing health impacts in Transport Appraisal

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Glossary/ Acronyms

Active Travel	Physically active modes of transport. Traditionally this means walking and cycling but can also include electric assist bikes (e-bikes), scooters, roller skates/blades, and other such modes.
CRA	Comparative Risk Assessment – a relatively simple health impact modelling method, alternatives are life tables (including proportional multistate life table, PMSLT) and longitudinal microsimulation.
DfT	Department for Transport.
DALY	Disability Adjusted Life Year. Measure of health burden compared against age specific 'ideal' life expectancy. DALY = YLD + YLL.
Domain	Physical activity is traditionally conceptualised as occurring across multiple domains e.g. leisure and occupational.
DRF	Dose response relationship. How a change in exposure changes the risk of an outcome over a range of exposure values.
GBD	Global Burden of Disease (provides data for all countries in the world and on age and gender specific burden (YLLs and YLDs) from a vast range of diseases. For England we have regional data available.
HEAT	The World Health Organization Health Economic Assessment Tool
HSE	Health Survey for England. HSE is an annual survey looking at the health and lifestyles of people all over the England.
ICT	Impacts of Cycling Tool (http://www.pct.bike/ict/) (Department for Transport funded project with Cambridge as lead academic institution).
Lag	The time between a change in exposure and a change in the risk of disease.
Life Table	A method for calculating changes to life expectancy following changes in age specific risk of death.

MET	Metabolically Equivalent Tasks. A body mass adjusted measure of energy expenditure.
mMET	the MET rate above the resting metabolic rate, i.e. the MET rate minus 1. This avoids including the background resting rate when estimating the volume of PA. Value of 1 is the resting metabolic rate.
MRC	Medical Research Council.
MVPA	Moderate to vigorous physical activity.
NTS	National Travel Survey designed to monitor long-term trends in personal travel and to inform the development of policy.
NVPA	Non-vigorous physical activity.
PA	Physical Activity.
PAF	Population Attributable Fraction. PAF is the proportional reduction in population disease or mortality that would occur if exposure to a risk factor were reduced to an alternative ideal exposure scenario
PCT	Propensity to Cycle Tool (http://www.pct.bike/) (Department for Transport funded project with Cambridge as lead academic institution).
PHE	Public Health England.
PMSLT	Proportional Multi State Life Table. An alternative to CRA. Preferable for allowing for competing causes of death and thus for calculating events over time. Allows incorporation of morbidity unlike a traditional life table.
QALY	Quality Adjusted Life Year.
RR	Relative Risks quantify the strength of effect of an exposure on an outcome.
VSL	Value of a Statistical Life (the metric currently used in WebTAG and HEAT).
VSY	Value of Statistical Life Year (e.g. DALY or QALY).
WebTAG	Transport analysis guidance from DfT.
WHO	World Health Organization.
YLD	Years Lived with Disability. One of two elements of DALY, together with YLL.
YLL	Years of Life Lost. One of two elements of DALY, together with YLD.

1. Introduction

This report describes a method to estimate the health benefits of walking and cycling interventions through physical activity. Method is illustrated by calculating impact for one scenario. The overall aim of this document is to provide input into the refresh of the WebTAG guidance for England on physical activity.

Before describing the method this report will provide background on what we know about physically activity and health; physical activity, transport and health; and how the health benefits of transport related walking and cycling are calculated (Part 2). Part 3 summarizes current methods used in

WebTAG and the WHO HEAT tool. Part 4 described proposed method to estimate walking and cycling related economic benefits and part 5 summarizes our recommendations and future research ideas. In the Appendix we describe alternative dose-response functions, uncertainties and run sensitivity analyses.

This report is accompanied by spreadsheet model that follows the recommendation from part 4 and Analytica model that contains all sensitivity analysis from Appendix.

2. Literature review

This section summarizes the current state and direction of the science on physical activity and health. The focus is on evidence relevant for estimate physical activity related health benefits from changes to how people travel. The review brings out issues that cannot be included within the forthcoming WebTAG update but which may be of relevance for future developments.

2.1. Physical activity and health

Physical activity is a complex multidimensional behaviour, which includes several sub-dimensions; frequency, duration, and rate of energy expenditure required to produce muscular work. The epidemiology of physical activity has developed over the past 60 years, from the first aetiological observations of differential rates of coronary heart disease in London bus drivers and conductors (Morris et al., 1953) to cohort studies linking individual exposures and outcomes (Paffenbarger et al., 1978) (Consortium, 2012; Wen et al., 2011). It is now widely accepted that an inverse association exists between physical activity and several disease outcomes, and a recent meta-analysis estimated physical inactivity to be responsible for 5.3 (of 57) million deaths worldwide, similar to the burden of tobacco smoking and obesity (Lee et al., 2012).

The majority of the evidence linking PA to health outcomes comes from cohort studies of self-reported PA and objectively measured health outcomes. In these studies groups of people answer questions about their PA and are then followed up over time allowing us to compare the disease event rates in people with different levels of PA. The findings from the studies are statistically adjusted to allow for other differences between the groups that might affect disease risk, e.g. smoking. Systematic reviews use explicit methods to search the research literature and include all the relevant studies of sufficient size and quality. These studies can then be quantitatively synthesised in meta-analysis in which results from multiple studies are statistically combined together to reduce the uncertainty one gets with any one study.

Studies combining a meta-analysis within a systematic review provide the best evidence linking physical activity to each health end point. Some meta-analyses include methods to estimate the dose response relationship, i.e. how much a unit change in PA leads to a change in the risk of disease.

A recent systematic review with meta-analysis found that physical activity was associated with lower risks of adverse outcomes including all-cause mortality, cardiovascular disease, ischemic heart, disease, stroke, depression, dementia, type 2 diabetes, total cancer, colon cancer, breast cancer, and lung cancer (Golubic, 2014).

Our confidence in a causal relationship between changes in PA and health outcomes is further enhanced by studies that have randomly assigned people to PA interventions. Such trial evidence is in principle stronger than observational evidence because other factors that differ between the groups should be averaged out through the process of randomisation. However, most of the randomised trials on physical activity are small and only look at shorter term outcomes. They are often conducted in high risk groups and in some cases combine physical activity interventions with other lifestyle interventions, such as dietary interventions. Broadly these studies show that increased physical activity reduces cardio-metabolic risk factors for chronic disease (such as blood pressure, cholesterol, and blood glucose) and also the risk of developing diabetes in high risk groups. (e.g. (Gillies et al., 2007)).Thus while these studies are of value in supporting a causal relationship they are of limited use in providing values that can be used in health impact modelling of changes to transport in the general population.

On the other hand cohort studies provide information about these relationships in the general population, and across a whole range of exposures. One limitation of this literature, as mentioned previously, is that the evidence from cohort studies overwhelmingly comes from self-reported PA. The many different tools used to measure PA vary considerably in what they cover and how active they find populations to be. However, we are beginning to see an evidence based emerging linking objectively measured PA to health endpoints. Already we have some evidence linking objectively measured PA to cardio-metabolic risk factors. The literature on hard disease end points will increase rapidly over the next few years due to studies such as UK Biobank in which objective PA has just been recorded on 100,000 participants (using accelerometers). Objective measures of activity typically include continuous monitoring over a week (which can be argued to be reasonably representative for that person's activity). As this evidence becomes available it will vastly improve the precision by which we can link PA to health outcomes. The overall picture of benefits from being physically active on the risk of chronic diseases will not change but the exact benefit from different doses of PA and the range of diseases associated may change, most likely towards bigger effects as measurement error in physical activity behaviours tends to attenuate associations.

However, even when we have objective data linking PA to hard health end points there will still be a challenge in using this for modelling population health outcomes. This is because our estimates of how active real world populations are will still be largely derived from self-report and other limited measures employed in routine surveillance systems.

One way to assemble a "complete record" from this self-report data is to map subjective data sources to objective data. This can be done in large datasets with both subjective and objective data. Based on this we can then map both the estimates used in the cohort studies and the estimates we have for the population under consideration. This is particularly important in the case of transport where we may be using representative travel surveys to estimate population levels of active travel. While such surveys are good at capturing walking and cycling behaviours they differ significantly from the surveys used to inform the cohort study estimates of the association between PA and disease risk.

Within the next couple of years it should be possible to do this by standardising the different self-report tools to an objective measure. This could perhaps be analogised to upscaling a TV signal from standard or high definition to 4K resolution; it should appear to be the same program (answer) and will gradually improve as 4K becomes the broadcast standard. As objective data from the cohort studies becomes available this can then become the source of our information on the dose-response relationships between PA and the various health outcomes. Eventually it should become possible to use new techniques to directly estimate the PA and change in PA of free-living whole populations.

2.2. Domains of physical activity

Physical activity can be conceptually separated out into different domains, usually leisure, work, and household. Transport is sometimes described as a separate domain and sometimes as part of leisure.

The self-report instruments used to measure physical activity were designed to facilitate the cognitive process required for recall, and therefore typically only include a small subset of the activities a person actually does, and in many cases only leisure-time activities. Occasionally, information about activities for transport is analysed separately or included in the summary measure for leisure-time activity but often not considered at all. It is also the case that activities that are used regularly by a minority in most countries, such as cycling, have a smaller evidence base than activities used more widely, such as walking. It is also the case that work related activity and some household related activities have traditionally not been measured well.

Although further research is still needed it is likely that the total amount of PA that an individual undertakes is more important than their activity in any one given domain.

2.3. Measuring of physical activity

The total volume of PA can be measured as METs hour or mMET hours per week. The MET component is a measure of the intensity of an activity, the rate of energy turnover per unit time; we multiply by time (hours per week) to calculate total energy spent in a week. When the focus is physical activity we used the unit mMET as the measure of the intensity of an activity; this only considers the energy turnover rate over and above the resting metabolic rate. Thus this allows us to combine time spent in activities of different intensity into one metric.

If we accept that there is a non-linear relationship between PA and health outcomes then to estimate how a change in PA leads to a change in disease risk requires estimating the total volume of PA of the individual, not just the volume in one domain.

Equally the observation of non-linearity also makes it more important that we accurately map the different tools used to measure PA in the population of interest to that used in the cohort studies. For example if one tool estimates the same population is twice as active as another then any change in the activity of the population will be estimated to produce a smaller change in disease risk when using the tool that gives the higher activity estimates.

Thus, whilst using non-linear dose response relationships is more realistic, it does require more care when applied to prevalence data or it may not produce reliable estimates of impact.

2.4. Dose response meta-analyses studies

Traditionally most of the meta-analyses looking at the association of PA and disease end points have reported a single effect estimate comparing high versus low activity populations. However, when modelling the health impacts of changes to active travel we need to know not just about the difference between high and low exposure groups but what the incremental benefits of a small change in PA are. The method for combining studies to estimate the association between different levels of PA and health outcomes is called a dose-response meta-analysis.

There are comparatively few dose response meta-analyses of PA. The MRC Epidemiology Unit is currently undertaking a series of dose-response meta-analyses looking at the relationship between leisure time PA and various diseases. We have published the analyses for type 2 diabetes in Diabetologia (see Figure 1 below). The remaining analyses on cardio-vascular diseases, cancer, mental health, and mortality will be completed over the next few months. The approach used in these meta-analyses has been to attempt to standardise as many of the self-report measures as possible to allow the inclusion of the largest possible number of studies in the final effect estimates. Although requiring more assumptions this has advantages of providing a single estimate to use, unlike other dose response meta-analyses that have produced multiple estimates based on different ways of measuring PA (e.g. (Aune et al., 2015)).

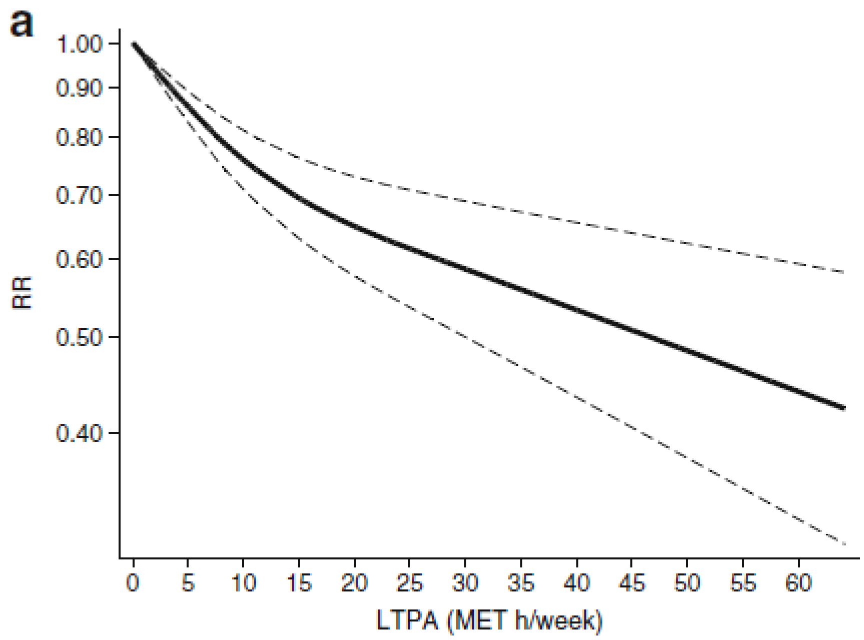

Figure 1: DRF relationship between LTPA and incidence of type 2 diabetes (Smith et al. 2016, Figure 2A).

Previously a systematic overview of the relationship between PA and health outcomes was published in (Woodcock et al., 2009) and a dose response meta-analyses looking at the association between walking and cycling and all-cause mortality were published in (Paul Kelly et al., 2014). The estimates from these studies have formed the basis of a number of subsequent health impact modelling studies (e.g. (Götschi et al., 2015; Maizlish et al., 2013; Woodcock et al., 2014), including the 2014 WHO HEAT tool (Kahlmeier et al., 2014).

The evidence from the largest individual studies and the dose response meta-analyses that have been completed clearly suggests that the relationship between PA and health outcomes is non-linear with the greatest benefits arising from increases in the least active people, e.g.(Wen et al., 2011;

Woodcock et al., 2011) (Aune et al., 2015)(Paul Kelly et al., 2014). This finding has important implications for how we choose to model PA.

2.5. Physical activity benefits and age

Age is an important consideration when modelling the health impacts of changes to PA. Mortality rates and the risk of most disease increase with age. However, the pattern is not uniform across all diseases. For example dementia risk increases rapidly at older ages, while depression affects a much wider age range.

If we use an impact metric based on counting deaths then a premature death at any age counts equally. However, using a metric based on life years recognises that a death at a younger age will result in more years of life lost than a death in old age. For morbidity it will depend on the disease duration, i.e. if it is shorter than expected life expectancy. If it is shorter then age is immaterial to the value of the health gain from averting the disease incidence.

The current use of mortality rates based on youth to middle age excludes the high death rates in the old and the low death rates in the young. It is unclear how users of WebTAG version 2014 currently handle behaviour change amongst older people and children. It might be suspected that they often have little information on the age of the population changing behaviour. It is also likely that for most cycling interventions behaviour change among older age groups is not the norm. Currently in England around 9% of cycling trips by adults are by those aged 65 years or over, this compares with 17% in the Netherlands. However, walking is much more common at older ages and some policies may affect age groups differentially.

Rather than using an average value that implicitly assumes no behaviour change amongst older adults a better solution would the use scheme specific data or if not available routine data on who walks and cycles at the moment. In the PCT we used routine data to apply age specific estimates from the Census 2011 on the cycling population and for the Go Dutch scenario on the age structure of Dutch cycle commuters. An approach that allowed inclusion of disease risk and mortality rates at all ages would be stronger than one based on a mid-life average if it could be supported by data.

It should also be noted that cycling is more common among men and walking among women and that men have higher mortality rates than women.

As well as older adults there is the more difficult question of how to include children. Thankfully children do not generally suffer from the diseases associated with inactivity. Furthermore among the few who do suffer from the same diseases the aetiology may differ (e.g. higher genetic component) and it cannot be assumed that increases in PA would reduce the disease risk to the same extent.

However, increasing PA in children is a part of the government's Cycling and Walking Investment Strategy and so is seen as important in policy and has public support.

Although clinical disease is unusual inactivity can still lead to a worse cardio-metabolic risk profile in childhood and adolescence. A systematic review found that there was moderate evidence that higher physical activity was associated with lower overweight and obesity, better motor skill development, and cognitive development in infants; while in toddlers there was moderate evidence of improved bone and skeletal health; and in pre-schoolers there was evidence of lower overweight and obesity, psychosocial health, and cardio-metabolic indicators (Timmons et al., 2012). Another systematic review, in older children, found evidence that physical activity reduced cholesterol, blood pressure, overweight and obesity, potentially improved bone mineral density, and may reduce risk of depression (Janssen and Leblanc, 2010). A pooled analysis of objectively measure PA data from multiple studies found that higher PA in children aged 4 to 18 was associated with improved cardio-metabolic risk factors but not with a lower waist circumference (Ekelund et al., 2012).

It is also likely that PA at a young age has an influence on behaviour in middle age, as habits are maintained or re-established later in life. However, modelling long term effects comes with considerable uncertainty, and will be very sensitive to the assumptions made on the maintenance of such behaviour. Furthermore, discounting will reduce the value of any such benefits.

Values used in economic appraisal come in the main from willingness to pay. Thus it may be appropriate for the future development of appraisal to look for alternative ways to give an economic expression the widely held view that children being active and not overweight is valuable.

2.6. Time Lags

The cohort studies that form the majority of the evidence base for PA typically measure PA at one point in time and then track the occurrence of health outcomes prospectively thereafter. These analyses implicitly assume that each individual remain at that exposure level for the duration of follow-up. Thus they tell us little about the time lag between a change in PA and a change in disease risk. Overall the evidence on the effects of change of PA is limited. The evaluation of exposure change requires repeated measurement of the exposure. Unfortunately even when we do have multiple measurements any difference between two measurements is a function both of true change over the time period plus a not insignificant error component which generally leads to an attenuation of the effect.

Currently WebTAG 2014 and HEAT assume a build up to full reduction in risk of premature death occurs over five years. In an earlier modelling study (Jarrett et al., 2012) we assumed a 3·2 year lag period before 50% of the effect on new cases was achieved (8 years before full effect achieved). For depression, ischaemic heart disease, and cerebrovascular disease, we assumed a delay of 2 years before 50% of the effect on new cases was achieved (6 years before full effect achieved). For dementia, breast cancer, and colon cancer, we assumed a delay of 17 years before 50% of the effect on new cases was achieved (20 years before full effect achieved). All-cause mortality is likely to be a combination of the different diseases, with the majority of the reduction in events coming from changes in cardiovascular disease.

While the cohort studies do not provide direct evidence there is some indication from other sources that benefits occur relatively quickly. If all other factors were kept constant (including diet and resting metabolic rate), increasing PA by a 20-min brisk walk (4 METs), it would take a 75-kg person about 3 months to lose 1 kilogram of body fat. There are also exercise intervention studies in people at high risk. Generally these have found changes in cardio-metabolic risk factors occur in a matter of months e.g.(Dickinson et al., 2006)(Umpierre et al., 2011). However, these are insufficient to provide a robust evidence base for health impact modelling of hard disease end points in the general population.

With intervention studies in the general population the situation is even more difficult as the affected population will change over the duration of the intervention.

2.7. Transport & physical activity

Transport provides an important opportunity for physical activity. Walking is already the most popular form of activity and is often maintained into older ages (Strain et al., 2016) Walking has been found to be the largest contributor to PA in all age groups and both sexes (apart from men 35-44) (Bélanger et al., 2011), although the contribution is sensitive to the relative value placed on different activities. (Roberts et al., 2016). Walking tends to increase with age in women. (Roberts et al., 2016). Regional differences exist in PA in England, with lower activity levels in the North (Roberts et al., 2016).

Cycling currently makes a much smaller contribution to population levels of PA, but it does make a major contribution to the PA of those that use it. Although there is potential to increase both walking and cycling in the population, cycling has considerably greater higher because of the low base (in most places) and the greater distance which can be covered on a bike. The potential reach of e-bikes could be greater still. However it does need to be recognised that achieving Dutch propensity to cycle would (all other things being equal) result in less walking. An analysis of the health benefits of the English population achieving the walking and cycling time of the Dutch and the Swiss found similar benefits from achieving the high cycling and lower walking time of the Dutch as with the high walking and medium cycling of the Swiss (Götschi et al., 2015). This was not a propensity analysis and so did not assume trip distances and numbers were a constant.

Recently stronger evidence is emerging that changes to the built environment can lead to mode shift (Heinen et al., 2015) (Goodman, 2013) and increases in PA (Panter et al., 2015) (Goodman et al., 2014). Findings from the Commuting and Health in Cambridge study suggest that increases in travel related PA are not compensated by reductions in other areas.

2.8. Measuring health effects: Disability-adjusted life years (DALY)

Global Burden of Disease (GBD) studies provide three measures of disease burden YLLs, YLDs, and DALYs. These metrics can all be described as health gap measures (Murray et al., 2000), that is the gap between the health of a population as it is against a reference population. The simplest metric is YLLs. For a given age group YLLs divided by deaths gives average expected life expectancy. YLDs are more complicated being based on a disease weight and a disease duration. DALYs are the sum of YLDs and YLLs.

The YLL and YLD values relates to the avoided events in one year. However, the benefits are then accrued over time. Thus the benefits can be described as occurring in one accounting year. To give an example if an average 40 year old person avoids dying in 2016 they gain an approximate extra 40 plus years of life. All of us must die but a death at any age from a preventable cause can be seen as premature and policy should aim to reduce such deaths. Because the YLL is based on age specific life expectancy this is recognised and there is a loss of life for a death at any age.

Traditionally in transport economics with a focus on road traffic injuries the relevant metric has been premature deaths averted. However, with physical activity and changes affecting the kind of chronic diseases that will eventually catch up with us all if we live long enough it may be more appropriate to consider the amount of extra life that is gained from an intervention.

When modelling YLLs changes to YLLs and YLDs it needs to be noted that YLLs gained will not all be in good health. Thus although there will be a direct reduction in YLDs through lower age specific risks because life expectancy will increase there will also more people at older ages when risks are higher. In consequence the number of people with a disease at one point in time may be higher or lower (noting that the total population size is now also larger). Care therefore needs to be taken if one adds YLD gains to YLLs without adjustment.

DALYs are not age weighted or discounted in the current version GBD. This followed considerable debate and criticism of the discounting applied in earlier versions (Mathers et al., 2013). It would be possible to apply discounting to YLLs as the length of time over which the benefit is accrued is known. However, without data on the disease duration it would not be possible to apply to YLDs. Age weighting would be one way to incorporate that years of life will not all be in good health and could be retrospectively applied to the data.

DALYs and QALYs are based on different conceptual principles. As mentioned previously a DALY is a measure of disease burden against a reference population and health gains are reductions in this disease burden. A QALY is a measure of additional years gained moving forward with no reference population. In practical applications the same value of a statistical life year has been applied to both DALYs and QALYs. We would recommend that decisions on if this appropriate should be taken at a cross departmental level.

2.9. Existing scientific health impact assessment models/assessment of active transport

Two recent systematic reviews, (Doorley et al., 2015)(Mueller et al., 2015) have reviewed and synthesized the recent development in active travel health impact assessment research. Below is a short summary of the key findings.

Mueller et al. (2015) reviewed studies conducting health impact assessment (HIA) of a mode shift to active transport on grounds of associated health benefits and risks. They identified 30 studies of which 18 were from Europe (four from UK), seven from US and five from Australia and New Zealand. Most of the studies (28/30) estimated the health effects through physical activity. Traffic injuries (21/30), air pollution (17/30) and noise (3/30) were other commonly estimated pathways. A variety of health impact modelling approaches and indicators were used.

In all studies that included PA the benefits were greater than the harms and in all but one study the physical activity benefits were main driving force behind the result (Figure 2 below). Mueller et al. (2015) concluded that "*net health benefits of active travel are substantial, irrespective of geographical context*". However, it should be noted that almost all the studies were in high income settings.

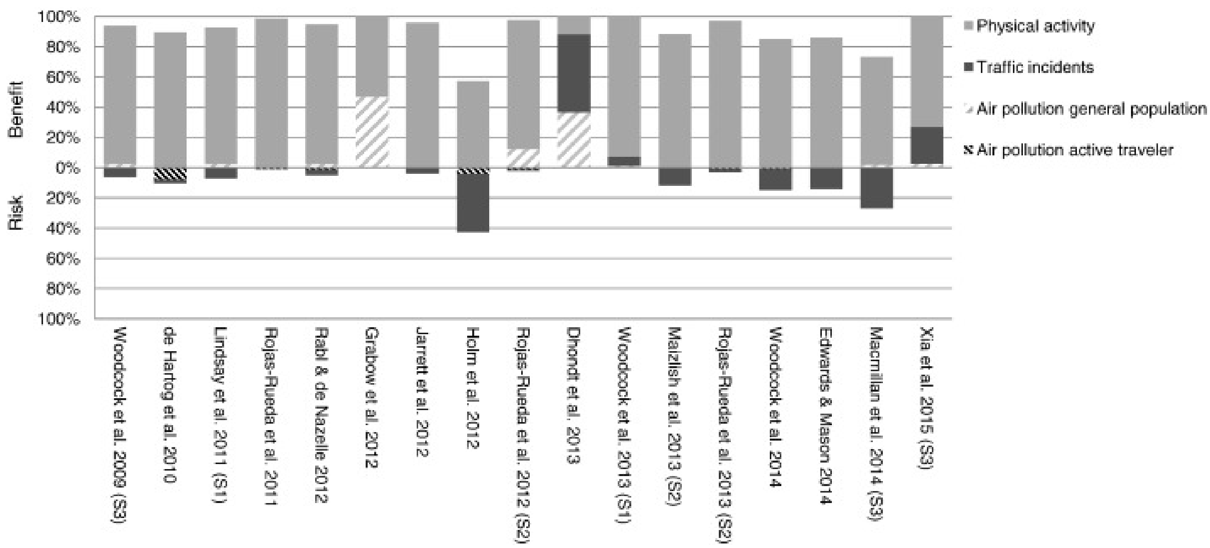

Figure 2: Figure 2 from Mueller et al. (2015) study showing different health pathways contribution to estimated health impact of a mode shift to active transportation for different studies.

Doorley et al. (Doorley et al., 2015) reviewed 19 studies, of which nine were considering pedestrian and 17 cycling scenarios. They also found that the results of the studies were dominated by the physical activity benefits. Of interest to this report they noted that the different approaches used to estimate physical activity benefits can lead to substantially different results. Doorley et al. (Doorley et al., 2015) identified that there is a need to further study and refine the relationship between physical activity and health for modelling studies.

3. Active mode health effects – current methods

3.1. Current Active mode appraisal

The current version of WebTAG includes guidance on how to predict the change in the risk of premature mortality due to active travel. The UK is ahead of most countries in including these important impacts within appraisal. The health economic benefits typically make up a substantial part of the business case for investing in walking and cycling. Thus improving the process for generating these estimates and making sure they are based on the latest and best evidence is critical.

The current approach to estimate active mode health benefits are described in TAG Unit A4.1 (Social Impact Appraisal) and TAG Unit A5.1 (Active Mode Appraisal). Unit A5.1 gives guidance on how to estimate and report impacts of active travel. Section 3 described the key impact of the active travel: (i) physical activity impacts, (ii) absenteeism impacts, (iii) journey quality impacts, (iv) accident impacts, (v) environmental impacts, (vi) decongestion and indirect tax impacts, and (vii) time saving impacts on active mode users. Details on how to calculate these impacts are in different TAGs. For example, the physical activity impacts (i) are described in TAG Unit A4.1. The appendix B describes some examples on how to calculate different key figures.

The physical activity impacts are calculated by using the relative risks of 0.72 for cyclists and 0.78 for pedestrians corresponding to 36 and 29 minutes of cycling and walking per day, respectively. These relative risks are based on Andersen et al. 2000 and WHO 2011, and are adopted from the WHO

Health economic assessment tools (HEAT) for walking and for cycling. The relative risks for cycling and walking above and below these durations are interpolated and extrapolated linearly as shown in the Appendix B of the TAG Unit A5.1.

The physical activity impacts are calculated using the mortality rate of the age group 15-64 year old, following the approach used in earlier version of the HEAT. The background mortality was assumed to be 0.0024 deaths, based on average mortality rate by ONS 2007. Gender and age differences are not directly taken into account. The economic impacts are calculated by multiplying the expected deaths with the value of a prevented fatality (£1,643,572 in TAG Unit A5.1 appendix example). To calculate the time spent walking and cycling, the cycling and walking speed are selected by the user but are not assumed to affect the intensity of the physical activity (thus a faster speed will lead to a shorter duration and smaller health benefit).

TAG Unit A5.1 also contains information on how to predict increase in the number of trips due to investment and how to turn these estimates to cycling and walking times. In the example in the appendix B new investment is assumed to generate 546 and cycling and 50 walking trip per day. To estimate the number of individual affected, 90% of the trips are assumed to be part of a return journey. The lengths of the trips are assumed to be 3.9 km and 1.15 km for cycling and walking trips, respectively, based on NTS data. Just over one quarter (27.3%) are assumed to replace car trips. The current approach also assumes 10% annual reduction in the walking and cycling after the initial investment.

3.2. WHO HEAT-tool

WHO's Health Economic Assessment Tools for walking and cycling (HEAT) is a tool developed to support evidence based decision-making and caters in particular to transport planners with little or no expertise on health matters and epidemiologic methods. HEAT is intended to be designed such that it should be universally applicable requiring only very basic input data on (changes in) walking or cycling. However, experience has found that users can sometimes still struggle with providing the data required.

Users can enter the amount of walking or cycling in various formats (i.e. duration, distance, trips, steps). Various input and/or default parameters then serve to convert the input data into estimates of long term walking or cycling estimates (i.e. days cycled per year, number or people to benefit). All parameters other than the input data on walking and cycling are provided as default values, with the option for users to enter their own data. For assessments of differences (e.g. between scenarios) or changes over time, the assessment is conducted twice.

The web interface does not allow users to enter the data in one page and simultaneously compare a range of scenarios. Because walking and cycling are considered separately any mode shift between these modes requires a separate HEAT calculation.

HEAT is being developed and continuously improved through an expert consensus process. At consensus meetings, a larger group of external experts and the core group discuss the next steps and aim to agree on key features and parameters of the new addition. The core group then tackles the technical implementation based on the decisions at the consensus meeting.

The WebTag 2014 method is based on an older version of HEAT. The most relevant changes adopted in the most recent version of HEAT are that current version uses relative risks for all-cause mortality of 0.9 and 0.89 for 11.25METhrs/week of cycling and walking, respectively, based on a recent meta-analysis of 14 studies on walking and 7 studies on cycling ((P. Kelly et al., 2014)). HEAT also provides an option to distinguish three crude age groups (young, all, elderly), which will result in the use of age-specific mortality rates. Aside from the updated RR estimates, this feature is likely to have the largest influence on the results (depending on how much an assessed population deviates from the general population in terms of age/mortality risk).

4. New proposed method

Below we will describe a new proposed method to estimate the health benefits of walking and cycling interventions through physical activity. The method is illustrated by calculating impacts for the same basic scenario as the one in **WebTAG unit 5.1 (Active mode appraisal)** document **Example Walking and Cycling Case Study in Appendix B** (page 13 onward in the document). The attached Spreadsheet model and the attached Analytica model uses this method to estimate physical activity benefits for cycling and walking.

The main upgrades we proposed are:

- To estimate health benefits for five different age groups and for both gender separately. The literature review and our earlier expertise (e.g. (Woodcock et al., 2014)) indicate that health benefits of physical activity vary by gender and age and therefore we want to introduce these for the calculation.
- The time spent walking and cycling is converted to METhs and the health benefits are calculated based on changes in METhs per week. This method will allow further development of the method by integrating different physical activities to same calculation.
- The RRs are based for the Kelly et al. meta-analysis that predicted cycling and walking specific changes in all-cause mortality. Kelly et al. forms the basis of the 2014 update of the WHO HEAT tool.

The main advantage of this approach is its simplicity. Mortality impact can be calculated without information from background physical activities making the calculation simpler than in other approaches (see appendix for illustration of alternative approaches). Method is also similar to the HEAT tool, making results more comparable. It is also flexible allowing for future improvements.

4.1. Estimating demand for scenario

The scenario in WebTAG unit 5.1 described an investment project that would increase cycling and walking. The project would start in year 2010 and be completed in 2012. Benefits are followed 20 years starting from the end of the project (until 2032). As described in Table B1 (WebTAG unit 5.1), the investment project is estimated to increase usage with 546 new cycling trips and 50 new walking trips per day. This is the main input data for the scenario.

From the number of new trips, the number of individuals affected by the project is calculated using the same methods as described in WebTAG unit 5.1. For all new trips, 90% of the trips are assumed to involve a return journey. Based on this assumption, the number of individuals affected by the project is calculated with the following equation:

Individual users = (546 new cycling trips * (90% / 2)) + (546 trips * 10%) = 300 users.

This is the number of new users after the investment is done. In baseline we assume that number of new users stay constant for the duration of the follow-up period In the Appendix we describe sensitivity analysis that take both decrease and increase in usage into account.

Note: WebTAG unit 5.1 also assumed small increase in baseline number of cyclists and pedestrians but this was not taken into account in these calculations.

4.2. Age and gender split

As described earlier in this report (chapter 2.5.), we wanted to take into account differences in health benefits by age and gender. The literature review and our earlier expertise (e.g. Woodcock et al., 2014) indicate that health benefits of physical activity vary by gender and age. Currently WebTAG does not recommend taking into account age or gender differences in the calculation. However, impacts are applied to mortality rates derived from a subset of the population (15-64 years old), following a similar approach to the WHO HEAT tool (Kahlmeier et al., 2014).

To estimate the age and gender distribution of the new cyclists and pedestrians, we multiplied the number of new users by the average age and gender split of cycling and walking trips, estimated from the National Travel Survey (NTS) (Table 1). The values in Table 1 are based on data analysis on current trips with a) walking and b) cycling as the main mode, and they showed that 74% of the cycling trips are done by males, and 55% by people in the age group 20-49. For walking, gender and age differences are smaller.

Clearly it is better to use scheme specific data if this is available from e.g. an intercept survey. Users also need to consider the nature of their intervention. For example an intervention targeted at commuters will mainly those of working age.

Table 1: Gender and age split of the observed main-mode cycle and walking trips in England NTS 2012-14.

	Cycling			Walking		
Age group	Male	Female	Total	Male	Female	Total
0-19	16%	4%	20%	15%	15%	30%
20-49	39%	16%	55%	17%	24%	41%
50-64	13%	5%	18%	7%	9%	16%
65-80	5%	1%	6%	5%	5%	10%
80+	1%	0%	1%	1%	1%	2%
Total	74%	26%	100%	45%	54%	99%

In the example scenario with 300 new cyclists and 27 new pedestrians we would have following age structure (Table 2).

Table 2: Age and gender split of new cyclist and pedestrians.

	Cycling			Walking		

Age group	Male	Female	Total	Male	Female	Total
0-19	48	12	60	4	4	8
20-49	117	48	165	5	7	11
50-64	39	15	54	2	2	4
65-80	15	3	18	1	1	3
80+	3	0	3	0	0	1
Total	222	78	300	12	15	27

4.3. Average time cycling and walking per person

We used the NTS data to predict the mean distance of cycling and walking trips by age and gender (Table 3). For both cycling and walking we excluded top 1% of the trips in order to limit the influence of outliers. See Appendix for sensitivity analysis results. Based on this data, the user can calculate increased time spent walking and cycling.

Again if the user has information on trip distances then these should be used in preference.

Table 3: Observed mean distance (miles per trip) of main mode cycling and walking trips in England NTS 2012-2014.

	Cycling		Walking	
Age group	Male	Female	Male	Female
0-19	1.81	1.55	0.68	0.64
20-49	3.73	2.49	0.74	0.67
50-64	3.92	2.33	0.76	0.73
65-80	2.79	1.71	0.73	0.68
80+	2.04	1.05	0.6	0.53

To calculate the mean distance per person we need to take into account the fact that 90% of the trips involve a return journey (as described earlier). This is calculated with the following equation (for 20-49 year old male cyclists):

Distance = (1-90% + 90% x 2) x 3.73 miles/trip = 7.09 miles per person per day

The health benefits of cycling and walking are calculated based on weekly activity. We estimate the average weekly activity by assuming that new users have 220 'active days' per year (active days refer to number of days (per year) that new user is assumed to be using e.g. new pathway). This same assumption is used in WebTAG unit 5.1. From this we estimate that average new user is active 4.22 days per week (220/365 * 7) and we calculate the total distance covered by cycling and walking by multiplying the average distance of the trip with the active days per week. For 20-49 year old male cyclists the calculation is following:

Distance cycled per week per person = 7.09 miles per person x 4.22 days cycled per week = 29.90 miles per person per week.

The estimated cycling and walking distances are converted to cycling and walking time by using the speed data from NTS. Table 4 described observed speed of main mode cycle and walking trips (miles/hour) in England, based on NTS 2012-2014. Also for this we excluded top 1% of the trips.

Table 4: Observed speed of main mode cycling and walking trips (miles/hour) in England NTS 2012-2014.

	Cycling		Walking	
Age group	Male	Female	Male	Female
0-19	6.12	4.45	2.55	2.53
20-49	9.12	7.22	2.74	2.6
50-64	8.91	7.07	2.62	2.49
65-80	7.48	5.99	2.49	2.35
80+	7.99	4.2	2.11	2.04

The total time spent cycling or walking is then calculated from this data by dividing the distance per week by the speed (e.g. for 20-49 year old male cyclists):

Time cycling per week = 29.90 miles per week per person / 9.21 miles/h = 3.28 h/week.

See Table 5 for average walking and cycling times per age and gender.

Table 5: Average cycling and walking times per person per. Unit: h/week.

	Cycling		Walking	
Age group	Male	Female	Male	Female
0-19	2.37	2.79	2.14	2.03
20-49	3.28	2.76	2.17	2.07
50-64	3.53	2.64	2.33	2.35
65-80	2.99	2.29	2.35	2.32
80+	2.05	2.00	2.28	2.08

4.4. Marginal METs

In most of the different dose-response models (see Appendix) time spent walking and cycling is converted to METs or marginal METs (see definition in Glossary) by multiplying the time spent walking and cycling with the average MET value of walking and cycling. Table 7 defines the average METs and mMETs used in the calculations. Both values are based on the updated 2011 Compendium of Physical Activities (https://sites.google.com/site/compendiumofphysicalactivities/) which combines current scientific knowledge on various physical activities impact to METs.

Table 6: Average METs and marginal METs used in the calculations.

	Cycling	Walking
MET	6.8	3.3

With the average METs we can estimate average physical activity increase in METh/week by multiplying the average cycling times with the average METs (e.g. for 20-49 year old males):

Average METh/week =3.28 h/week x 6.8 MET = 22.29 METh/week.

Table 7 shows the average METh/week and mMETh/week used in these calculations.

Table 7: Average MET and mMET increase per person due to cycling and walking.

	Cycling		Walking	
	MET		mMET	
Age group	Male	Female	Male	Female
0-19	16.12	18.99	7.05	6.69
20-49	22.29	18.80	7.14	6.82
50-64	23.98	17.96	7.67	7.76
65-80	20.33	15.56	7.76	7.65
80+	13.92	13.63	7.52	6.87

4.5. Dose-response function and population-attributable fraction

The mortality impact was calculated using the relative risks (RRs) for all-cause mortality for walking and cycling. These RRs are based on Kelly et al. 2014 study which estimated RR for walking and cycling, as well as different shapes of the dose-response relationship. From the RRs reported in the article we used the log-linear RRs. For walking and cycling the RR per 11.25 METh/week activity were 0.90 (95% confidence interval 0.85-0.95) and 0.90 (0.86-0.94), respectively (see Figure 3 for illustration). These RRs are assumed to sufficiently take into account other forms of physical activity so that we can estimate health benefits of cycling and walking directly, without taking other forms of physical activity into account. Benefits are capped for RR values of 0.70 and 0.55 for walking and cycling, respectively, following similar approach used in HEAT (WHO 2014). See Appendix for other possible methods.

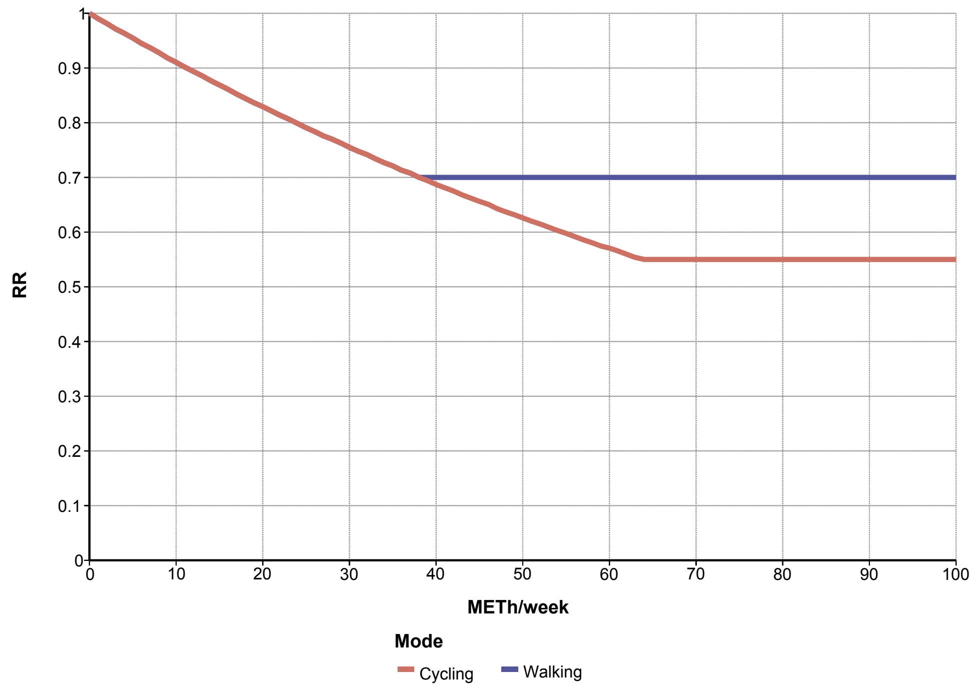

Figure 3: Illustration of the DRF for walking and cycling, based on Kelly et al. 2014. Benefits are capped for RR values of 0.70 and 0.65 for walking and cycling, respectively, following similar approach used in HEAT (WHO 2014).

Based on these RRs the change in mortality for the scenario was calculated with following equation:

Change in mortality = exp((ln(RR))/11.25 METH/week) x scenario METh/week)

For 20-49 year old male cyclist, using the values in Table 7, the change in background mortality would be:

RR for given cycling level = exp((ln(0.90) /11.25) x 22.29) = 0.81.

From this RR we calculate population attributable fraction (PAF) with equation:

PAF = (1.0-RR)/1 = 1-RR = 1.0-81 = 0.19

Thus, this scenario assumes that 19% of all-cause mortality could be avoided in this age and gender groups if those new users cycled an additional 3.28 h per week (Table 5).

4.6. Number of deaths and YLLs

The number of deaths avoided by age and gender was estimated by multiplying the change in background mortality with the background mortality for that age and gender group. Table 8 shows the background mortality rates data for the UK population. Death rates were calculated by dividing number of deaths in given age and gender groups with the total population of that groups. Data was obtained from the Global Burden of Disease 2015 study results for England. For comparison, current WebTAG unit 5.1 uses average mortality rate of 0.0024, which is average for age group 15-64 in England and Wales.

Table 8: Background mortality rates by age and gender, and the current background mortality rate used in the WebTAG unit 5.1.

Age group	Male	Female
0-19	0.00042	0.00032
20-49	0.00118	0.00071
50-64	0.00627	0.00419
65-80	0.02459	0.01669
80+	0.11471	0.09948
…	…	…
WebTAG unit 5.1 (2014) mortality rate	0.0024	0.0024

At this stage of calculation we assumed that cycling and walking would not decrease mortality in the youngest age group (0-19) by setting the mortality impact for that age group to be zero.

The resulting number of deaths avoided for year 2012 is presented in Table 9 for our example scenario. The number of deaths avoided were converted to YLLs by estimating from GBD 2015 study the average YLL loss of one death. To account effect of discount, these YLLs were discounted so that the YLLs gained in future were discounted with same 1.5% discount as economic benefits (see later chapter). Number of YLLs could then be estimated by multiplying the number of deaths with discounted YLLs. The discounted and undiscounted YLLs for each age and gender group are presented in Table 10.

Table 9: Number of deaths avoided per year due to increased cycling.

Age group	Male	Female	Total
0-19	0.00	0.00	0.00
20-49	0.03	0.01	0.03
50-64	0.05	0.01	0.06
65-80	0.06	0.01	0.07
80+	0.04	0.00	0.04
Total	0.18	0.02	0.20

Table 10: Average discounted and undiscounted YLL loss per death, predicted from GBD 2013 study results for England.

	Discounted YLLs		Undiscounted YLLs	
Age group	Male	Female	Male	Female
0-19	47.7	48.0	81.7	82.8
20-49	34.1	33.6	47.2	45.9
50-64	23.7	23.7	28.9	29.0
65-80	15.1	14.3	16.6	16.3
80+	5.8	5.8	6.4	5.7

4.7. Economic impacts and discount

The YLLs were converted to monetary impacts by multiplying the YLLs with the costs of life year value of £60 000. This value was proposed by DfT after the Initial project report in June 2016. The future monetary benefits were also discounted by using 1.5% discount rate, proposed by DfT. The discounting for each follow up year was estimated by following equation:

Discount % in given year = ((1/(1+1.5%))^number of years).

Table 11 shows the discount percentage for each year and the total economic health benefits for each year for cycling.

Table 11: Economic benefits for the cycling in the given example scenario. The project is assumed to start 2010 and be fully operational in 2012.

Year	Effectiveness of the infrastructure	Discount	Number of deaths avoided	Number of YLLs avoided	Economic benefits
2010	0%	100%	0.00	0.00	£ -
2011	0%	99%	0.00	0.00	£ -
2012	100%	97%	0.21	3.92	£ 228,476.34
2013	100%	96%	0.21	3.92	£ 225,099.84
2014	100%	94%	0.21	3.92	£ 221,773.25
2015	100%	93%	0.21	3.92	£ 218,495.81
2016	100%	91%	0.21	3.92	£ 215,266.81
2017	100%	90%	0.21	3.92	£ 212,085.52
2018	100%	89%	0.21	3.92	£ 208,951.25
2019	100%	87%	0.21	3.92	£ 205,863.31
2020	100%	86%	0.21	3.92	£ 202,820.99
2021	100%	85%	0.21	3.92	£ 199,823.64
2022	100%	84%	0.21	3.92	£ 196,870.58
2023	100%	82%	0.21	3.92	£ 193,961.16
2024	100%	81%	0.21	3.92	£ 191,094.74
2025	100%	80%	0.21	3.92	£ 188,270.68
2026	100%	79%	0.21	3.92	£ 185,488.35
2027	100%	78%	0.21	3.92	£ 182,747.15
2028	100%	76%	0.21	3.92	£ 180,046.45
2029	100%	75%	0.21	3.92	£ 177,385.66
2030	100%	74%	0.21	3.92	£ 174,764.20
2031	100%	73%	0.21	3.92	£ 172,181.48
2032	100%	72%	0.21	3.92	£ 169,636.93
Sum			**4.48**	**82.38**	**£ 4,151,104.13**

Total monetary benefits for this) scenario (including also walking) are £4.2 million, after discounting. In the WebTAG unit 5.1 scenario the total benefits of same scenario were estimated to be £1.3 million. The main reason for this difference is that in WebTAG unit 5.1 scenario 10% annual reduction for walking and cycling was assumed. If we assume 10% annual reductionin number of new users, this method would estimate benefits of £1.9 million (see appendix).

Thus, this method estimates larger economic benefits. This is mainly because the calculation takes into account health benefits of older age groups, while the earlier calculation did not take into account benefits for age group over 64 years old. Table 12 bellows shows how the benefits of the scenario divide between age and year. The second oldest age group (65-80) contributed 29% to total health benefits, despite only making 6% of cycling trips.

Table 12: Percentage of the benefits by different age groups.

Age group	Kelly et al. 2014 log-linear
0-19	0%
20-49	28%
50-64	37%
65-80	29%
80+	7%
Total	100%

5. Conclusions and future directions

In this report we propose and illustrate a refreshed method to calculate the physical activity benefits of walking and cycling. Based on our expertise on the health impact assessment of walking and cycling, and to most recent literature, we proposed that the WebTAG Unit 5.1 will be updated with following fashion:

1. Calculation would involve benefits for all adults, including people 65 years old or older.
2. Calculation would take into account age and gender split of current cyclists and pedestrians, assuming that this provides information on who is likely to take up walking and cycling.
3. The calculation would include information on trip distances and speed of cyclists and pedestrians to calculate time spend cycling and walking more precisely.
4. To calculate health benefits by converting the time spend cycling and walking to METs. This will allow future development of the method with more updated dose-response functions, currently under preparation in MRC Epidemiology unit (Cambridge).
5. To calculate YLLs by multiplying number of avoided deaths with the average YLL saved by age and gender to that age group.

Our comparison of results and sensitivity analysis (see appendix) showed that the calculation of economic benefits is sensitive to some of the input values and assumptions. The calculation was highly sensitive to the annual reduction of users (see appendix) and our results propose that this value should be further examined.

Our sensitivity analysis also showed that assumed active days per year is an important input value for the calculation. Current value is 220 days a year, based on number of the working days per year. As described in WebTAG 5.1, this is conservative assumption and doesn't take into account weekend travel.

The simplest approach to better quantify this value would be to use continuous count data (one year of daily counts) from any counter location (preferably several nearby of similar facility type) that count biking and walking. From this data user could calculate the ratio of "counts during your short term count period" and the annual average at the counter location. This method can include other variables, such as weather, or derive adjustment factors for weekday and month. See for example Lindsey et al. 2016 paper for description how to estimate effect of temperature, precipitation, wind speed, dew point, and hours of daylight. Online Trail Traffic Calculator tool (http://www.railstotrails.org/our-work/research-and-information/trail-modeling-and-assessment-platform/trail-traffic-calculator/) can be applied to estimate these values from existing travel data.

5.1. Future development

Based on the timeline agreed with the Department within this project

<u>End December 2016</u>

- We have not included the loss of PA from a switch from walking to cycling. We can include this.
- We have only applied discounting to the year in which a death occurs, not to the future live years gained from that death. If desired we can include this.
- The DfT is responsible for organising an expert advisory group. We are happy to help with recommendations on who should be invited.

<u>End March 2017</u>

We can produce a version of the Excel model for use on the web. An alternative would be to develop the model to include all the rest of the WebTAG calculation. This would require a small additional project and a little more time.

At this point a decision will be needed by DfT about which version (Excel, Analytica, R) that you want us to work on for the final deliverables.

<u>End May 2017</u>

We can produce regional level propensity estimates and offer these as an alternative for users. We can also make recommend cations for how the approach can be included within the PCT and ICT.

<u>End July 2017</u>

We have used calculations based on all-cause mortality. We can compare this against disease specific mortality using the new (unpublished) relative risks we have identified. As indicated in appendix this change is likely to produce smaller results.

<u>Beyond the project</u>

This method describes how the physical activity benefits can be calculated by estimating changes in YLLs. In future we would also like to involve diseases, expressed as YLDs. The meta-analysis that we are currently preparing in MRC Epidemiology Unit will give us dose-response data to do this update or alternative estimates can be used. However, the relationship between physical activity and disease burden is not as straightforward as between physical activity and mortality. Therefore before applying disease specific YLD to the calculation, we propose doing comparative modelling where we would compare the results of simple comparative risk assessment calculation (similar as described here) to the proportion multi-state life-table (PMSLT) model that estimates more realistically relationship between physical activity and diseases. If these two methods provide different results, as we assume, we can provide conversion factors that would allow to correct this error in comparative risk assessment calculation. We are happy to present on this approach to the expert group that the DfT will organise.

A further improvement that could be made is to use regional or even local authority level estimates of non-travel physical activity, and disease burden. We anticipate this will make a relatively small difference compared with other choices in the model but it may encourage local decision makers in the relevance of the approach.

A further issue for discussion is the lack of benefits for getting children cycling and smaller benefits from women cycling. Getting children active and reducing gender inequity are both widely seen as good things and the Department may want to consider additional ways to recognise this in the appraisal process.

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Appendix – description of sensitivity analysis

We performed a number of sensitivity and what-if analyses for the values used in this calculation to see how sensitive the model is to input value uncertainty and differences in model assumptions (e.g. dose-response functions). The sensitivity analyses were done with the Analytica version of the model using Monte Carlo simulation.

The sensitivity analysis was done in two steps: First, we identified uncertain input values and defined uncertainty distribution for them. Second, we calculated tornado plot sensitivity analysis by calculating the model with low and high estimate of each input value separately.

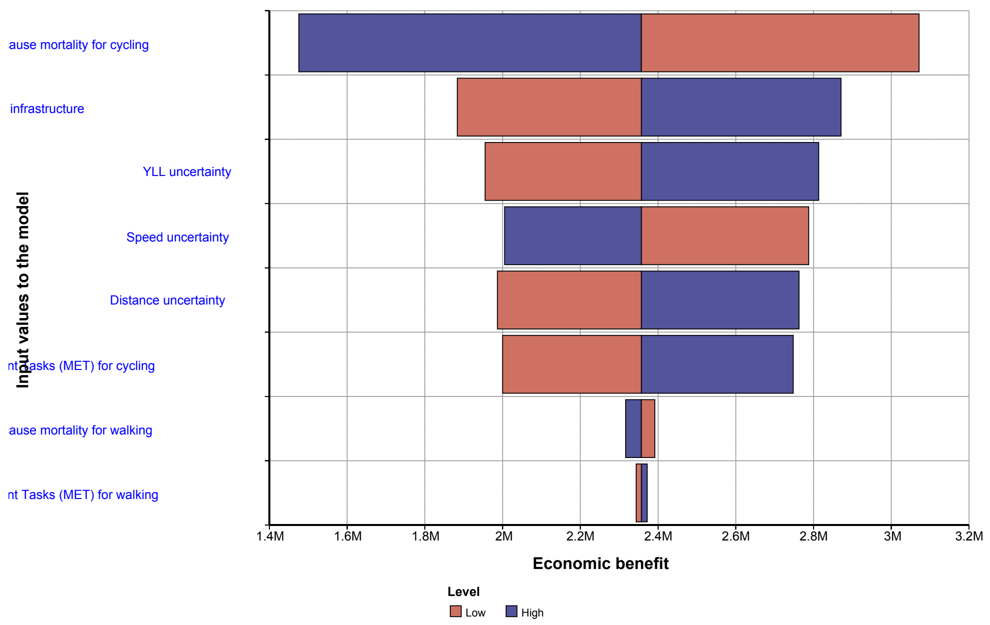
Below is the list of the uncertain input values that we identified and defined in the model:

- Return journey uncertainty: In baseline 90% of the trips are assumed to involve return journey through same road. In a sensitivity analysis +/- 10%-unit uncertainty is assumed for the return journey (i.e., the percentage of people doing return journey is assumed to be between 80% and 100%).
- Active days per year: In baseline new cyclists and pedestrians are assumed to be active 220 days per year. For uncertainty we assumed low estimate of 150 days per year and high estimate of 290 active days per year.
- Speed uncertainty: For mean speed by age and gender (Table 4) we assumed +/- 25% uncertainty.
- Distance uncertainty: For mean distance by age and gender (Table 3) we assumed +/- 25% uncertainty.
- MET uncertainty: For METs we assumed +/- 25% uncertainty around the mean estimate (Table 6).
- YLL uncertainty: For YLL we assumed +/- 25% uncertainty around the mean estimate (Table 10).
- RR uncertainty: For RR uncertainty we adopted the uncertain distribution from Kelly et al. by assuming normal distribution. See section 4.5. for values.

Figure A1 shows the results for tornado plot sensitivity analysis where the result of the model is compared with low and high estimates of different input values. The largest uncertainty was related to RR for cycling, adopted from Kelly et al. 2014 study. This is in line with our earlier studies where the uncertainty of RRs usually dominates the sensitivity analyses. In this example RR for walking had insignificant impact because number of new pedestrians were assumed to be small. The assumed number of active days per year, which is used to estimate the number of days the person is expected to cycle or walk per week, also had a large impact to results.

Among the other uncertainties, the model was not sensitive to the MET uncertainty for walking or cycling and only moderately sensitive to other input uncertainties.

Figure A1: Results of the tornado plot sensitivity analysis.



What-if calculations

We also performed a set of what-if calculations to see how model structure or alternative methods would impact the results. These are described below.

Alternative dose-response functions (DRFs)

For alternative DRFs we estimated the benefits based on Woodcock et al. 2011, a new meta-analysis currently prepared in MRC Epidemiology unit, and the WebTAG 5.1. (2014) methods. The WebTAG 5.1. (2014) method is based on the RRs adopted from earlier version of the HEAT tool and the results resembles the current WebTAG unit 5.1 calculations that would involve older age groups, and take into account age and gender differences in cycling and walking rates and speed. See details of these methods below.

<u>Woodcock et al. 2011</u>

Woodcock et al. 2011 study estimated RR for non-vigorous physical activity (NVPA) by systematically reviewing the literature between all-cause mortality and NVPA. Physical activity was aggregated to marginal METs, described earlier. The RR per 8.6 mMETh/week changes in physical activity was associated with RR of 0.81. Woodcock et al. 2011 also examined shape of the dose-response function and predicted different shapes. These are so called power-transformations which vary between 1 (nearly linear) and 0.25 (most curved).

The calculation of the RR was done with the equation:

RR = RR per 1mMETh per week ^(mMETh per week in scenario ^ Power-transformation)

For 10 mMETh/week with power-transformation of 0.50 the RR would be:

RR = 0.94 ^ (10 ^ 0.50) = 0.82

The challenge for WebTAG is that to use these RRs the user would need to know all the NVPA done by individuals who walk and cycle (so called background physical activity). For this we can estimate the background variation in physical activity by using the Health Survey for England (HSE) 2012 physical activity questionnaire. Using this data we could estimate a representative sample of mMETh/week values. To calculate the PAFs, we first add scenario mMETh/week values to background mMETh/week values and calculate PAF for the differences. See Table A1 for a sample of the background mMETh/week data for different age groups and the background mMETs/week for the cycling scenario (see Table 7). This data has been obtained by combining sport, walking and gardening activities together and aggregating this background physical activity to mMET/week values.

Table A1: Background mMETh/week values for the English male 20+ year old population, based on HSE 2012 physical activity questionnaire.

	Background				**Scenario**			
Individual	**20-49**	**50-64**	**65-80**	**80+**	**20-49**	**50-64**	**65-80**	**80+**
1	26	87	10	0	48	111	30	14
2	3	34	29	0	25	58	49	14
3	29	0	10	0	51	24	30	14
4	16	0	0	0	38	24	20	14
5	1	0	0	0	23	24	20	14
6	11	19	15	0	33	43	35	14
7	9	0	6	0	31	24	26	14
8	75	0	0	0	97	24	20	14
9	100	0	31	0	122	24	51	14
10	23	0	0	0	45	24	20	14
11	50	2	14	20	72	26	34	34
12	13	0	0	20	35	24	20	34
13	26	0	0	7	48	24	20	21
14	0	19	0	0	22	43	20	14
15	30	0	0	0	52	24	20	14
16	28	0	0	0	50	24	20	14
17	2	6	40	0	24	30	60	14
…	…	…	…	…	…	…	…	…
1000	0	15	0	0	22	39	20	14

The RRs were calculated for each individual with the equation:

RR = RR per 1 mMETh/week ^ (scenario mMETh/week ^ Dose-response shape)

The PAFs were then calculated by following equating:

PAF = (average $RR_{Background}$ – average $RR_{Scenario}$) / average $RR_{Scenario}$

Rest of the calculation follows similar pattern as in the main example.

<u>New meta-analysis in MRC Epidemiology unit (unpublished)</u>

MRC Epidemiology unit researchers have done a new systematic meta-analysis and dose-response synthesis of current physical activity literature to estimate the RRs for different exposure levels. Table A2 below shows an example for this data for the 0 to 10 mMETh/week exposure to physical activity. In this data the benefits of physical activity continued until 77 mMETh/week, with no further benefits of increasing physical activity beyond that level. That doesn't mean that in reality there would not be any benefits beyond this, but our data was too uncertain after that point.

Table A2: RR for different mMETh/week values in new, unpublished meta-analysis.

mMETh/week	**RR**
0	1.00
1	0.96
2	0.92
3	0.89
4	0.86
5	0.83
6	0.80
7	0.78
8	0.77
9	0.75
10	0.74

The RRs were calculated similarly to the Woodcock et al. 2011 method by using the background and scenario mMETs/week (Table A1) and calculating PAFs by comparing population before and after the scenario. See Table A3 for the resulting PAFs by age and gender.

Table A3: PAFs for walking and cycling based on new meta-analysis results, for the example scenario.

	Cycling		Walking	
Age group	Male	Female	Male	Female
0-19	0.29	0.30	0.17	0.17
20-49	0.16	0.18	0.09	0.11
50-64	0.22	0.21	0.12	0.12
65-80	0.24	0.23	0.13	0.14
80+	0.25	0.26	0.15	0.16

<u>WebTAG 5.1. (2014) method</u>

The WebTAG 5.1. (2014) method assumed that the reduction in relative risk for cyclists is 0.28 (relative risk of 0.72) at 36 minutes per day and for walkers is 0.22 (a relative risk of 0.78) at 29 minutes per day for seven days a week. These benefits were assumed to reach their maximum after 36 and 29 minutes of cycling and walking per day for cycling and walking, respectively, and the relationship between RR and walking/cycling time was linear. We used same calculation by adopting scenario specific cycling and walking times from Table 5, and divided this walking and cycling time with average number of active days to week to give daily estimate. See Table A4 for the PAFs by using this method.

Table A4: PAFs for age, gender and mode, following WebTAG 5.1. (2014) method.

	Cycling		Walking	
Age group	Male	Female	Male	Female
0-19	0.17	0.21	0.14	0.13
20-49	0.23	0.20	0.14	0.13
50-64	0.25	0.19	0.15	0.15
65-80	0.22	0.17	0.15	0.15
80+	0.15	0.14	0.15	0.14

<u>Different DRFs - results</u>

The results for different DRFs with using same scenario as described in the text are shown in Table A5. All the alternative methods estimated larger benefits, up to 24% more if we used RRs from the Woodcock et al. 2011 study. The new meta-analysis results, that will be published in near future, showed similar health benefits with the WebTAG 5.1. (2014) method. Based on these results we assume that method proposed in the report is conservative and health benefits could be higher with other methods. However, differences are still small, when compared to other uncertainties.

Table A5: Economic benefits with different DRF assumptions.

DRF method	**Monetary benefits**	**Comparison to Kelly et al. 2014 (Baseline)**
Kelly et al. 2014 log-linear	£ 4,151,104.13	100%
Woodcock et al. 2011 non-linear	£ 5,211,462.18	126%
WebTAG 5.1. (2014) method	£ 4,942,367.89	119%
New MRC Epidemiology unit meta-analysis results	£ 5,020,345.25	121%

Lag

WebTAG unit 5.1 (2014) uses five year lags to estimate physical activity benefits due to cycling and walking. The method presented in this report is without lag because we consider scientific evidence of lag to be too weak to include it to calculation. To investigate how possible lag would have changed the results, we rerun the results with 0, 3, 5, 10 and 15 year lags (Table A6). The results indicate that, when compared with the baseline assumption of no lag, the results would be 13% smaller with 5 year lag (as used in WebTAG unit 5.1 (2014).

Table A6: The results of the scenario with 0 to 15 year lags.

Lag	Economic benefits	% change
No lag (baseline)	£ 4,151,104.13	100%

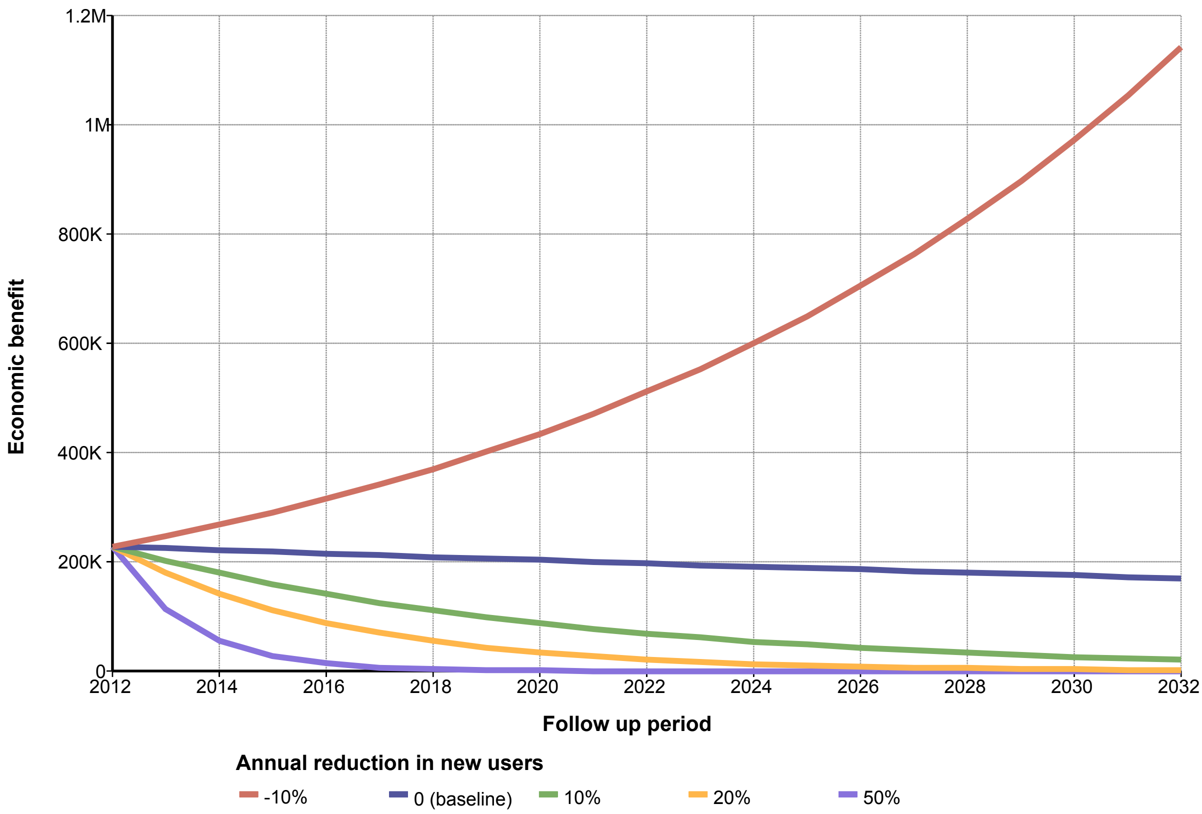
3 years	£ 3,905,395.23	94%
5 years	£ 3,667,639.55	88%
10 years	£ 3,095,447.76	75%
15 years	£ 2,551,743.63	61%

Decrease in usage

In WebTAG unit 5.1 example scenario it was assumed that usage of new infrastructure will decrease by 10% every year. This was described as a conservative assumption. In this report we assumed that usage is constant after the investment.

We illustrated impact of usage changes by calculating the annual benefits of cycling and walking with different reduction estimates, starting from -10% (i.e. cycling and walking is increased 10% every year) to 50% reduction every year. Figure 5 shows the results for individual years. The results vary from £12.0 million (10% increase is usage) to £0.5 million (50% reduction per year). With the 10% annual reduction the health benefits would be £1.9 million. As noticed in the WebTAG unit 5.1, the decision on changes in annual usage have significant impact for the results.

Figure A2: Annual monetary benefits per year with different annual reduction estimates. Baseline assumption was 0% reduction (blue line below).



Dutch age and gender split

We also tested the calculation by using the age and gender split of cycling trips based on Dutch national travel survey data. This what-if analysis represents the situation in a high cycling culture area where the gender and age differences in cycling are smaller than in UK. Table A7 shows the data. With Dutch age and gender data the economic benefits would be £3.9 million (compared with £4.2 million in baseline). Further sensitivity analyses would be needed to examine this further but our current estimation is that omitting of the health benefits for youngest age group (0-19 years old) and more even gender split reduced overall benefits.

Table A7: Observed split of main-mode cycle trips in Dutch NTS 2012-14 by age and gender.

Age group	**Male**	**Female**	**Total**
0-19	18%	16%	34%
20-49	15%	21%	36%
50-64	8%	11%	18%
65-80	5%	5%	10%
80+	1%	1%	1%
Total	46%	54%	100%

Different cut-off points for NTSS data

For calculation of the mean distance cycled and walked (Table 3) was calculated by omitting top 1% of the trips. For sensitivity analysis we calculated the results by assuming no cut-off and by using 10 and 25 mile cut-offs for walking and cycling, respectively. The results are shown in Table A8. As assumed, no cut-off increased average distance of the trips and consequently economic benefits. However, changes are small indicating the our calculation is not sensitive for this cut-off value.

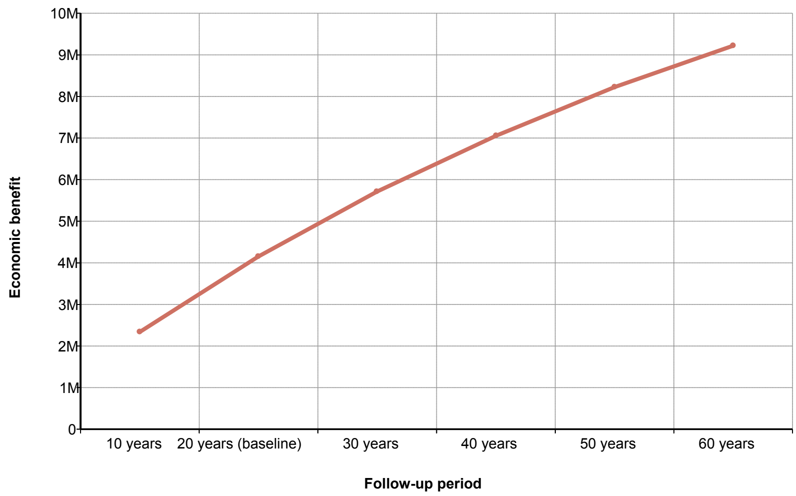
Table A8: Economic benefits with different cut-off assumptions.

1% cut-off (baseline)	£ 4,151,104.13
No cut-off distance	£ 4,392,816.46
25/10 mile cut-off	£ 4,196,144.69

Follow-up time

The last what-if analysis tested the impact of the follow up period by varying the follow-up time between 10 and 60 years (baseline value was 20 years). Figure A3 shows the results. Although this calculation took into account discount of the economic benefits, the benefits increase nearly linearly when the follow-up time increases. With 60 year follow-up the benefits of the scenario would be £9.2 million, indicating that follow-up time is significant uncertainty for the calculation.

Figure A3: Total economic benefits for different follow-up periods.



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