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Assessment of Methodologies for Quantifying the Health Impacts of Active Travel

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Abstract

In the past several years, active travel (walking and cycling) has been increasingly recognised as an effective means of increasing physical activity and mitigating negative external impacts of motorised transport. As a result of this recognition, a range of methodologies for quantifying the benefits and risks of active travel have emerged in the literature. This review critically assesses studies which quantify the health impacts of transport scenarios involving increased active travel. It was found that the choice of methodology and assumptions employed in such studies may have a significant impact on the results and so care must be taken when planning these studies or interpreting their results. Increases in physical activity are the most important determinant of the health impacts of active travel but different methodologies for quantifying the health impacts of this physical activity can lead to substantial differences in the scale of the impact. Therefore, further research is required into the relationship between increased physical activity and health effects. Particular attention should also be paid to ensure that health impacts are assessed for both the individuals changing their travel behaviour and all other individuals in the study area. Where relative risk relationships are used to estimate health impacts, researchers should be mindful of the specific exposures used to develop these relationships in order to prevent double counting of health impacts. Extensive sensitivity analysis is necessary to compensate for the uncertainty inherent in models for predicting health effects.

1. Introduction

In recent years, active travel (human powered modes such as walking and cycling) has been recognised as an effective means of increasing physical activity levels and contributing to physical and mental health. The World Health Organisation's (WHO) Global Recommendations on Physical Activity for Health (WHO, 2010) has recommended that adults should engage in at least 150 minutes of moderate-intensity aerobic physical activity throughout each week. Active travel provides an ideal opportunity to incorporate such levels of moderate intensity physical activity into the daily routine and evidence has shown that programmes of active travel are more sustainable than other forms of exercise (Dunn et al., 1999). Active travel also brings a number of important external benefits to society through the replacement of motorised transport in the network. Although users of active travel may also be exposed to additional risks such as increased inhalation doses of toxic pollutants (McNabola et al., 2008, Zuurbier et al., 2010) and increased risk of being a victim of a traffic collision, the overwhelming scientific consensus is that these risks are far outweighed by the benefits (Cavill et al., 2008, Teschke et al., 2012).

While people generally place a high value on their health and years of life, traditional cost benefit analyses of transportation projects do not take health impacts into account. In the past decade however, there has been a growing interest in the "Health in All Policies" (Leppo et al., 2013) approach to public health, whereby implications for health and health equity are considered in policy making across all sectors. In the context of active travel, this approach requires methods for quantifying the health impacts of active travel and there is a growing body of literature around these methods. In 2008, a review of cost benefit analyses of transport infrastructure and policies considering the health benefits of active travel was carried out (Cavill et al., 2008) where the authors found significant heterogeneity in the approaches taken in such analyses and recommended a more "harmonised approach" to the quantification of the health impacts of active travel. This led to the development of the Health Economic Assessment Tool (HEAT) for cycling and walking. The

simplicity and transparency of HEAT makes it a very convenient tool for decision makers who may not be equipped to quantify health impacts of changes in travel patterns and this has led to wide usage both by researchers and governments. However, HEAT is only focussed on a single determinant of health, physical activity, and does not attempt to address other important benefits and detriments of active travel on the basis that other impacts should be dealt with separately. More recently, many studies have been published which assess other impacts of increased active travel in addition to physical activity and there has been considerable variability and opacity in the approaches taken. This makes it difficult to interpret the results of previous assessments or to plan a new assessment based on best practice, particularly for transport planners who may not be experts in public health.

This paper contributes to the field by providing an overview and assessment of recent approaches to quantifying the health impacts of active travel, with an emphasis on the methodologies employed. Particular attention is paid to areas where a strong consensus in methodology does not yet exist. The paper is organised as follows. Section 2 describes the search strategy and inclusion criteria for the review. Section 3 discusses the methods which may be used to define a study scenario involving increased active travel such that a quantitative assessment is possible. In Section 4, the different outcome measures which may be used in an assessment are discussed. In Section 5, each of the determinants of health related to active travel and the methodologies by which they may be quantified are examined in turn. A brief overview of the results obtained by the studies under review is given in Section 6. The paper concludes with some discussion of the most important findings and recommendations for future work.

2. Search Strategy

Studies were sought for inclusion in this review which had performed a quantitative assessment of the health impacts of a real or simulated transport scenario involving increased active travel and included health outcomes such as mortality, life expectancy or Burden of Disease (BOD) in their

analysis. A comprehensive search of English-language literature was carried out using the Web of Knowledge, Science Direct and PubMed databases. Searches were conducted using different combinations of keywords such as HIA, active, travel, transport, risk, assessment, cycle, walk, health, cost, benefits, mortality, morbidity, HEAT, quantification etc. using multiple variations of key words where appropriate. The search was supplemented with studies known to the authors. Studies were screened for relevance by title and/or abstract. In some cases, studies were initially chosen for inclusion but excluded after being reviewed in full. An emphasis was placed on studies published since 2008. For studies prior to 2008, the reader is directed to Cavill et al. (2008) which provides a convenient summary.

3. Study Scenarios

An overview of the nineteen studies considered in this review is given in Table 1. Nine of the studies considered changes in walking and seventeen considered changes in cycling. The study scenarios in the papers considered can be grouped into five broad categories: studies where actual data from a bike-share scheme was used; studies where a sub-population underwent a hypothetical change in travel behaviour; studies where the entire population underwent a hypothetical change in travel behaviour; studies where an activity based travel analysis (Axhausen and Gärling, 1992) simulated a change in behaviour at the level of individual activities and one study which simulated the impacts of policy changes using System Dynamics Modelling (SDM) .

One approach to defining a study scenario is to simply use actual data. However, in many cases reliable data regarding use of active travel is unavailable. Cycle hire schemes are a notable exception as they can provide reliable disaggregate information on the cycling patterns of a population in response to the introduction of the scheme. The first quantitative assessment of health impacts of

such a scheme was conducted by Rojas-Rueda et al. (2011) to evaluate the public bike sharing initiative, Bicing, in Barcelona, Spain. It was assumed that 90% of the trips made by Bicing users were new cycling trips which would have otherwise been made by car. However, this assumption has been criticised by Fishman (2011) who states that the available data show that only 9.6% of Bicing trips substitute for a car journey and so, that study probably overestimated the benefits of the scheme. Fishman et al. (2012) also evaluated the benefits of the Bicing scheme but used publicly available reports to estimate not only the number of trips and distance travelled per day, but also the proportions of these trips which were new trips and which substituted for trips by walking, private bike and other modes. A more recent study by Woodcock et al. (2014) evaluated the London bicycle sharing system, taking advantage of detailed user data. The modal shift attributable to the use of the scheme was estimated from survey responses from registered users which prevented unrealistic assumptions about the proportion of trips which were replacing car trips.

As shown in Table 1, the most commonly used approach for defining scenarios in the studies reviewed was to consider a situation where some portion of current or future trips undertaken by motorised transport was shifted to active travel and/or public transport. This approach assumes that a small sub-population can make a fundamental change to their travel behaviour without any change to the behaviour of the rest of society. Three studies, (Maizlish et al., 2013, Woodcock et al., 2009, Woodcock et al., 2013)considered more holistic changes in travel behaviour whereby, instead of an isolated sub-population switching from motorised travel to active travel, the distribution of times spent in active travel across the whole population was shifted positively. Current and hypothetical transport scenarios being considered were used to derive mean distances walked and cycled per year and per week. Lognormal distributions (because distributions of time spent walking and cycling are non-negative and are empirically known to have long tails on the positive side of the peak) were fit about these means to give age-specific and sex-specific active travel-time distributions. A characteristic of all of these hypothetical approaches is that they give the

assessment little value as a policy formulation instrument as no consideration is given to the courses of action which may help policymakers to achieve the scenarios.

Two of the studies reviewed (de Nazelle et al., 2009, Dhondt et al., 2013) however, evaluated specific interventions by simulating travel behaviours before and after the intervention using activity based travel analysis. de Nazelle et al. (2009) developed a custom MATLAB® model, BESSTE (Built Environment Stochastic Spatial Temporal Exposure), to simulate travel activity patterns before and after a built environment transformation. Activity diaries were generated for each simulated individual from the Environmental Protection Agency's (EPA) Consolidated Human Activity Database (CHAD). The home locations and locations of daily activities were then decided by a stochastic selection process subject to a gravity model, which models attraction between origins and destinations by an analogy to Newton's gravitational formula (de Dios Ortuzar and Willumsen, 1994). The mode choice taken to access each destination was then selected using a logit model. A Monte Carlo simulation was used to simulate many individuals for 365 days. Dhondt et al. (2013) simulated travel activity patterns before and after an increase in the cost of fuel using the FEATHERS (Forecasting Evolutionary Activity-Travel of Households and their Environmental Repercussions) model, whose activity scheduling engine is based on decision trees derived from activity diary data. FEATHERS uses these sequential decision trees to predict at an individual level where and when specific activities are conducted and - if transport is required - the mode taken, for a simulated "statistical duplicate" of the population. Origin-destination matrices are then extracted from the simulated activity patterns, together with mode of transport, and iteratively assigned to the road network. These activity based models have greater potential for the evaluation of transport policies or interventions than methods which simply define hypothetical transport scenarios without considering the instruments which may affect such changes. However, they are much more data and resource intensive and so, may not be suitable for many practical applications.

Macmillan et al. (2014) were unique in their use of SDM to simulate three policy scenarios. SDM is a field which incorporates knowledge of strategic decision making and feedback loops into simulation

of complex bounded systems (Richardson, 2011). Using this framework, Macmillan and colleagues developed equations to simulate the effects of three intervention policies based on quantitative and qualitative research and local data. Feedback effects such as improvements in infrastructure in response to increases in cycling rates were also incorporated into their simulation.

Figures 1 and 2 show a guideline of the various processes which were used for translating these study scenarios and interventions into quantified health impacts. In order to keep the diagrams compact, not every variation in these processes has been shown but the figures should give the reader an idea of the modelled pathways. These processes are discussed in sections 4 and 5.

4. Health Measures

Table 2 shows the health summary measures which were the outcomes of interest in the studies reviewed. Although choice of transport mode can affect many aspects of both mortality and morbidity (Garber et al., 2011, US DHHS, 2008, WHO, 2011), many of the studies reviewed neglected the impacts of the additional active travel on morbidity. HEAT (Rutter et al., 2013), the most widely used tool for estimating the health effects of walking and cycling was used to estimate health effects in several of the studies in this review, considering the economic value of changes in mortality as the only outcome. As outlined in Rutter et al. (2013), evidence regarding all-cause mortality is considered to be more robust and so, the inclusion of morbidity would lead to greater uncertainty in the results of an assessment. Despite the apparent reliability of using all-cause mortality at the outcome variable, it can be expected that exclusion of the effects of morbidity in assessments of the health impacts of active travel would lead to less precise results. For example, non-fatal traffic injuries can result in many years spent in poor health or with disability (Holtslag et al., 2008) which would be ignored if only mortality is considered. It should also be noted that addressing morbidity has been identified as the single most important improvement to be made to HEAT in future revisions (WHO, 2011). However, focussing on mortality only may still be preferable in some cases.

For example, when the aim is to influence policy, conservatism and transparency may be more important than precision.

Several of the studies reviewed did consider morbidity as an outcome variable in addition to mortality. BOD is a summary measure of the impact of a disease on global health which takes into account both years lost and years spent in poor health. The BOD approach was taken by six studies. Several other studies quantified individual health events such as hospitalisations or incidence of cancer.

If mortality was the outcome variable, estimated changes to mortality rates could be used to directly estimate the reduction in number of deaths per year using a static approach or to calculate the resulting changes in life expectancy using a life tables approach. If BOD was the outcome variable, it was measured in Disability Adjusted Life Years (DALYs). DALYs can be considered as the sum of Years of Life Lost (YLL) and Years Lost Due to Disability (YLD). YLDs are calculated as the product of the duration of a condition in years and a "disability weight", where a weight of 0 implies perfect health and the worst disabilities approach a weight of 1.

As shown in Table 2, several of the studies reviewed also calculated equivalent monetary benefits for the estimated health benefits. If the health outcome considered was static mortality rate, the reduction in mortality could be translated to an equivalent monetary benefit using the Value of a Statistical Life (VSL). This is the method used in the HEAT methodology. An advantage of VSL is that it is the most commonly used measure in transport appraisals and so it provides coherence and consistency with other estimates of mortality impacts. If the life tables approach was employed, the equivalent monetary benefit could be calculated using the Value of a Life Year (VOLY). None of the studies reviewed which considered DALYs as the health outcome calculated an equivalent monetary benefit. As contended in Desaigues et al. (2011), VOLYs are a more appropriate measure of the cost of mortality due to air pollution and physical activity. The strongest argument for this is that VSL is calculated with regard to accidental deaths which generally lead to many more years of life lost than

deaths due to chronic pollution exposure or physical inactivity. Therefore, if VSL is used to monetise the mortality effects of pollution exposure or physical activity, the results are likely to be overestimated. This leads to the approach taken by Rabl and de Nazelle (2012) where the change in mortality due to air pollution and physical activity were monetised in VOLYs while deaths due to traffic collisions were monetised using VSL. The values used for VSL and VOLY are chosen at the discretion of the researcher and these values vary widely, particularly between Europe and North America. For example, Grabow et al. (2012) used a VSL of $7.4 million whereas Olabarria et al. (2013) used a VSL of € 1.3 million. Fishman et al. (2012) used simple per km estimates of health benefits for walking and cycling from the New Zealand Transportation Agency Economic Evaluation Manual (New Zealand Transport Agency, 2010) but it is unclear how the estimates were calculated. In addition to the costs of morbidity and mortality, several studies quantified the impact on actual health care costs (Gotschi, 2011, Grabow et al., 2012, Lindsay et al., 2011). However, where health care costs were considered, they were considered alongside morbidity and mortality costs, which were generally the main focus of these studies.**5. Determinants of Health**

5.1 Physical Activity

All studies reviewed included changes to physical activity levels as a determinant of health. As outlined in Table 3, physical activity levels could be described in terms of distances, times, metabolic equivalent of task (MET) hours or energy expenditure. These measures could relate to walking, cycling or engaging in any physical activity. In most cases, the change in physical activity was based on an estimated or hypothetical conversion of a particular portion of trips to cycling and/or walking and so the calculation was trivial. Gotschi (2011), however, estimated future miles bicycled from projected future bicycle counts by estimating the ratio between bicycle miles and bicycle counts for short trips in 2005 and assuming this ratio would remain constant. Where the change in physical activity was based on a shift in active travel time distribution for the entire population under study, a more complex approach was taken. In Maizlish et al. (2013), Woodcock et al. (2009) and Woodcock

et al. (2013), the travel-time distributions were converted to MET hours per week using a compendium of published MET values for various activities (Ainsworth et al., 2011, Ainsworth et al., 2000). Median values of each distribution (or each quintile of each distribution) were then added to estimates of median non-travel activity MET hours from survey responses to obtain median MET hours per week for total physical activity. Dhondt et al. (2013) also converted the estimated total distance and number of trips made by active travel estimated by the FEATHERs activity-based model to age and sex specific MET time distributions. Similarly, Woodcock et al. (2014) created separate lognormal distributions for four domains of physical activity; bike-share cycling, other cycling, walking and other physical activity. Between the actual scenario and counterfactual scenario (if the bike-share had not been introduced), the bike-share cycling was assumed to increase by the amount observed in the bike-share data while other cycling and walking decreased by the amount assumed to have been displaced by the bike-share programme. For each scenario, total physical activity was modelled as a stochastic combination of the four distributions. de Nazelle et al. (2009) calculated the energy expended by each simulated individual during each activity of each day as the product of the individual's simulated body mass, the MET value associated with the activity and the time spent in the activity. The MET values were stochastically drawn from probability distributions of MET values for that activity, found in the EPA's CHAD.

Various approaches were used across the studies to translate changes in physical activity to health benefits. The majority of these considered physical activity or walking and/or cycling as continuous variables and used published RRs and Dose-Response Functions (DRF) to determine the impact of the additional physical activity on a summary health measure. If the amount of physical activity being considered was different to the amount on which the published RR was based, the RR needed to be corrected using the DRF. This includes eight studies which calculated reductions in all-cause mortality using the approach of HEAT (Gotschi, 2011, Grabow et al., 2012, Lindsay et al., 2011, Olabarria et al., 2013, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012, Deenihan and Caulfield,

2014) and several studies which calculated reductions in mortality using RRs and/or DRFs from other sources (Dhondt et al., 2013, Hartog et al., 2011, Rabl and de Nazelle, 2012, Macmillan et al., 2014). Five studies (Maizlish et al., 2013, Rojas-Rueda et al., 2013, Woodcock et al., 2009, Woodcock et al., 2013, Woodcock et al., 2014) used the WHO's Comparative Risk Assessment (CRA) approach which involves estimating the change in DALYs due to specific diseases using RRs and DRFs. Conditions such as dementia, cardiovascular diseases, type II diabetes, breast cancer, depression and colon cancer were considered. Since the exposure variable in these cases was total physical activity, it was necessary to also estimate non-travel physical activity.

Other studies considered physical activity as a categorical variable. de Nazelle et al. (2009) quantified health impacts of the change in physical activity by creating distributions of the fraction of days per year that individuals exceeded recommended levels of physical activity as defined by the USDHHS,1996 (US DHHS, 1996). Holm et al. (2012) considered the number of persons who could be classed as being "sufficiently active", "moderately active" or "inactive" based on guidelines from the WHO. RRs of five specific diseases between each pair of these categories of physical activity from the WHO's Comparative Quantification of Health Risks study (Bull et al., 2004) were used to calculate the change in DALYs attributable to the movement of individuals from one category to another.

As most of these studies relied on the use of RRs and DRFs from previous studies for their calculations, the uncertainty inherent in these data was an important consideration. Several studies, in sensitivity analysis, incorporated the confidence intervals of the published RRs into their models using Monte Carlo simulation (Dhondt et al., 2013, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012, Macmillan et al., 2014) or by using the upper and lower limits of the intervals directly (Holm et al., 2012, Rabl and de Nazelle, 2012). Others modified the shape of the DRF by assuming a log-linear relationship between the RR and various transformations of the exposure variable (such as power of ½ or ¼) rather than the untransformed exposure variable (Rojas-Rueda et al., 2013, Woodcock et al., 2009, Woodcock et al., 2013, Woodcock et al., 2014). Some also applied a completely different

model to the one used in their main analysis (Woodcock et al., 2013) or changed their exposure variable from distance to MET hours (Rojas-Rueda et al., 2011), or their outcome variable from DALYs to mortality (Rojas-Rueda et al., 2011, Woodcock et al., 2013, Woodcock et al., 2014). These sensitivity analyses consistently show that different modelling techniques of the health impact of physical activity produce very different results and highlight the need for a consensus on the most reliable approach.

5.2 Air Pollution

Pedestrians and cyclists do not produce any air pollution while travelling and thus, a modal shift towards active travel has the potential to decrease societal exposure to air pollution. However, persons switching from motorised travel to active travel may be exposed to higher inhalation doses of air pollution during travel time due to higher ventilation rates (McNabola et al., 2008, Panis et al., 2010, Zuurbier et al., 2010). Therefore, both individual and external effects of air pollution should be considered in quantifying the health impacts of a modal shift. However, as shown in Table 4 most of the studies considered in this review only based their analysis on one or the other.

Exposures to a range of particulate and gaseous pollutants were considered as determinants of health in the studies reviewed, including PM2.5, PM10, carbon monoxide (CO), sulphur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3) and elemental carbon (EC). There is strong evidence that PM2.5 exposure is associated with increased long term risks of all-cause, cardiopulmonary, and lung cancer mortality. There has also been some evidence of effects of gaseous pollutants such as CO, SO_2, NO_2 and O_3 on long term mortality. However, evidence has shown that, apart from SO_2, the effects of these gaseous pollutants on mortality become non-significant when controlling for PM2.5 exposure and other covariates (Brook et al., 2010, Chen et al., 2008, Krewski et al., 2005, Pope et al., 2002). The recent decline in the use of high-sulphur coal for domestic heating has led to large reductions in levels of sulphur dioxide in the U.S.A. and many European countries (US EPA, WHO,

2005) and thismay be why SO_2 was not considered in any of the studies reviewed. The most commonly considered pollutant in the studies reviewed was PM2.5. However, some other pollutants were also considered as shown in Table 4.

In sensitivity analysis, several studies such as Rojas-Rueda et al. (2011), Rojas-Rueda et al. (2012) and Hartog et al. (2011) analysed the effect of a pollutant not considered in their main analysis. . Some studies also considered the possibility that traffic-related particulate matter (PM) is more toxic than typical ambient PM on which exposure-response functions in the literature are based (Hartog et al., 2011, Rojas-Rueda et al., 2011).

5.2.1 External Impacts of Air Pollution

The first step taken in each study for calculating the avoided external cost of air pollution was to estimate the avoided emissions of various gaseous and particulate pollutants, usually using an emissions prediction model. A number of emissions modelling software packages were used in the studies reviewed but the most common was the COPERT 4 model; a software tool which calculates average emission factors and total mass of air pollution and greenhouse gas emissions from road transport (Emisia, Kousoulidou et al., 2008) based on data such as fleet characteristics and meteorological information.. Woodcock et al. (2013) took a more simplified approach to this step by using published emissions factors.

In some cases, the external impacts of the avoided emissions were estimated directly by using cost estimates from previous studies. . Rabl and de Nazelle (2012) combined the emissions results from COPERT 4 with the results of the ExternE study of the external costs of energy (ExternE) which reported damage costs per tonnes of transport emissions for various cities. Lindsay et al. (2011) and Macmillan et al. (2014) estimated the total morbidity and mortality impacts of their study scenario by using the results of the HAPiNZ study (Fisher et al., 2007) which estimated the morbidity, mortality and health costs associated with road vehicle emissions in New Zealand.. Other studies

modelled the pollutant concentrations resulting from the change in emissions using an atmospheric dispersion model and estimated the impact of the change in population exposure. A range of commercial and non-commercial dispersion models were used but it is outside the scope of this study to discuss these in detail. Several reviews have already been devoted to the discussion of such models (Holmes and Morawska, 2006, Jerrett et al., 2005). Woodcock et al. (2013) used a simpler approach for this step, assuming that the change in transport related emissions would translate to a proportional change in ambient concentrations of primary PM2.5 attributable to transport. The concentration changes (or population –weighted concentration changes) of pollutants, estimated by a dispersion model or another method, could then be used to calculate the impacts on mortality (Hartog et al., 2011, Rojas-Rueda et al., 2012) or BOD (Rojas-Rueda et al., 2013, Woodcock et al., 2009, Woodcock et al., 2013, Maizlish et al., 2013) using published RRs and DRFs for different levels of pollution exposure or by using specialised software (Grabow et al., 2012).

Similar to the DRFs for physical activity, there were uncertainties associated with the published DRFs for pollution exposure used in these studies. In some cases, the responses of these models to variations in the RRs were tested using Monte Carlo simulation (Dhondt et al., 2013, Grabow et al., 2012, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012) or by testing the upper and lower confidence limits of the RRs directly (Holm et al., 2012). Rabl and de Nazelle (2012) created confidence intervals for the damage costs of air pollution analytically by assuming an approximately lognormal distribution, as described in a separate publication (Spadaro and Rabl, 2008).

5.2.2 In-travel Air Pollution Exposure

Several of the studies reviewed considered the impacts of a change to in-travel exposures to air pollution for the travellers changing their mode of travel. Dhondt et al. (2013) calculated the change in "dynamic exposure" for the population by taking an average of the concentrations of each zone at each time step, weighted based on the proportions of each zonal population exposed to each concentration (Dhondt et al., 2012). In the rest of the studies which considered in-traffic pollution exposures, the methods used to assess the impact of in-travel pollution exposure were similar and based on inhaled dose rather than concentration. de Nazelle et al. (2009) estimated inhaled doses of PM10 and ozone by simulated individuals by integrating the product of stochastically determined minute ventilation rate (VE) and modelled pollutant concentration level over time for each activity throughout each simulated day . Other studies used similar approaches but estimated the VE and pollutant concentrations in different ways. The three studies by Rojas-Rueda and colleagues obtained average exposure concentrations for each mode from previous studies (de Nazelle et al., 2011, de Nazelle et al., 2008). Hartog et al. (2011) and Rabl and de Nazelle (2012) took typical urban European concentrations and applied scaling factors to account for differences in exposure concentrations between modes. Woodcock et al. (2014) used data on 24-hour average PM2.5 concentrations at $20m^2$ resolution to estimate in-travel PM2.5 concentrations at the route-specific level and applied scaling factors to account for differences between each mode. A scaling factor used for trips on the London Underground to account for the possibility that PM2.5 underground may be less harmful to health than surface level PM2.5 (Seaton et al., 2005). Holm et al. (2012) assumed constant in-travel concentrations for all modes based on average values from two street monitoring sites.

The three studies by Rojas-Rueda and colleagues also obtained inhalation rates for each mode from previous studies (de Nazelle et al., 2011, de Nazelle et al., 2008). Hartog et al. (2011) and Holm et al. (2012) estimated the ventilation rate during cycling to be 2.2 times that of driving or resting based on the average of ratios reported by two studies (Vanwijnen et al., 1995, Zuurbier et al., 2009). Rabl

and de Nazelle (2012) and Woodcock et al. (2014) assumed ventilation rates were proportional to MET rates. .

The health impacts of short time periods spent in differentially polluted environments and inhalation doses of pollutants have not been studied extensively. For this reason, all of the studies which estimated health impacts using inhaled dose did so by calculating an "equivalent" long-term change in average concentration using the ratio of the time-averaged inhalation doses for the alternative scenarios. The impact on mortality or BOD could then be calculated using concentration-response functions for all-cause mortality or specific diseases from the literature (Krewski et al., 2009, Pope et al., 2002, Ostro, 2004, Beelen et al., 2008). This meant that the inhalation dose during the non-travel daily activities also had to be estimated. This was done by assuming that non-travel time was spent in low intensity activities while exposed to typical ambient concentrations. Of the nine studies which analysed in-travel pollution exposure, only two based their calculations on pollutant concentrations measured during travel (Rojas-Rueda et al., 2012, Rojas-Rueda et al., 2013). However, studies have shown that fixed monitoring stations can significantly underestimate or have little or no association with the exposure of commuters (Adams et al., 2001, Gulliver and Briggs, 2004). For this reason, future studies should consider taking in-travel measurements of pollution exposure where possible. It is also important to note that studies which use HEAT or directly use the RR from Andersen et al. (2000) to calculate the mortality impact of increased physical activity, are also including the mortality impact of increased pollution exposure in this calculation. Since the Andersen RR is based on a cohort study which did not adjust for air pollution exposure; it is probable that the mortality benefits of physical activity were offset by the effects of increased pollutant inhalation. Therefore, as outlined in the HEAT user guide, it may not be necessary to separately account for the effects of increased inhalation of pollutants. However, several of the studies reviewed (Rabl and de Nazelle, 2012, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012) used this RR and also accounted for in-travel exposure to air pollution, and thus may have double-counted. This may be justifiable, for

example, if the study region has significantly higher pollution levels than Copenhagen or if the authors wish to be conservative in their analysis but such assumptions should be made explicitly.

5.3 Traffic Collisions

In most transport environments, where modal share of active travel is low, pedestrians and cyclists face a greater risk of injury or death due to traffic collisions than motor vehicle users (Elvik, 2009) and cycling is perceived as being less safe than driving (Lawson et al., 2013). Many of the studies reviewed considered only the change in risk for the individuals who changed mode and assumed the risk was unchanged for those who did not. Six studies (Hartog et al., 2011, Holm et al., 2012, Rojas-Rueda et al., 2011, Rojas-Rueda et al., 2012, Rojas-Rueda et al., 2013, Woodcock et al., 2014) took this approach by using historical collision data to derive the risk of a collision per unit distance for each mode under study. Dhondt et al. (2013) used a similar method but stratified by conflict type. Such methods are unrealistic and likely to overestimate the increase in traffic collisions due to increased active travel for a number of reasons. Firstly, research has consistently shown a "Safety in Numbers" effect associated with active travel modes (Elvik, 2009, Jacobsen, 2003, Robinson, 2005) meaning that as distances travelled by cycling and walking increase, the risk of road traffic injury for pedestrians and cyclists decreases. For example, (Robinson, 2005) reported that "If cycling doubles, the risk per kilometre falls by about 34%" and (Jacobsen, 2003) reported that "An individual's risk while walking in a community with twice as much walking will reduce to 66%". Secondly, while active modes may sometimes be at high risk of being victims of road traffic collision, their risk of being the striking vehicle in road traffic collision is low. The replacement of motorised vehicle kilometres with active travel kilometres, therefore, reduces the rate of collision risk for all other travellers.

One of the studies reviewed, (Lindsay et al., 2011) accounted for the "Safety in Numbers" effect by first estimating the risk of traffic injuries and fatalities for motorised transport and cycling using historical collision data and then applying a correction factor to the cycling collision rates based on the aforementioned empirical estimate of (Jacobsen, 2003). However, this empirical correction does

not account for the reduction in risk to the remaining users of all other modes due to the reduction in vehicle km travelled. Woodcock et al. (2009) used an elaboration of a traffic injury model described by Bhalla et al. (2007) to estimate the absolute numbers of road traffic collisions at the city level for all modes of transport after a modal shift. A traffic injury matrix was constructed for each road type and level of injury severity where the cells of each matrix contained the historical number of traffic collisions for each pairwise combination of striking mode and victim mode (e.g. the number of pedestrians injured by cars). To estimate the numbers of injuries after a modal shift, it was assumed that the number of injuries for each striking-victim pair was proportional to the distance travelled by the striking mode and to the distance travelled by the victim mode. In their sensitivity analysis, they changed the injury rates per km walked and cycled to those of the Netherlands where modal shares of walking and cycling are already high and injury rates are low. Although this approach accounts for changes in collision risk for all modes after a modal shift, the proportionality assumption in the main analysis ignores evidence of a non-linear relationship between distance travelled and road traffic injuries (Elvik, 2009). Woodcock et al. (2013) and Maizlish et al. (2013) took a similar approach but introduced non-linearity by using power transformations of the exposure variables (distances). As the degree of the non-linearity of injury risk is not well established, both Maizlish and Woodcock tested the sensitivity of these models by using a range of exponents of the distances travelled. Macmillan et al. (2014) also elaborated on the model of Bhalla et al. (2007) but only considered collisions between light vehicles and bicycles, ignoring other modes. Based on longitudinal collision data for the study area, they assumed a linear relationship between cycling trips and cycling collisions up to a threshold modal share of 2.5% after which a “Safety in Numbers” effect of half that recommended by (Jacobsen, 2003) was applied. A power transformation based on Turner et al. (2009) accounted for the non-linear impact of the number of light vehicles. Another factor which can confound predictions of road traffic injuries is underreporting of injuries in the baseline data. This is especially true for cycling as many cycling injuries are not recorded by police (Doherty et al., 2000, Stutts et al., 1998). Woodcock et al. (2014)

corrected their injury data for underreporting of injuries by applying London-specific scaling factors for each mode from published data comparing police data and hospitalisation rates. Rojas-Rueda et al. (2013) also corrected their bicycle injury data in sensitivity analysis using generic European scaling factors recommended by the HEATCO project (Bickel et al., 2006).

For studies where mortality was the health outcome considered and only fatal injuries were modelled, the calculation of health impacts from the change in traffic injuries was trivial. In several studies where BOD was the outcome considered (Holm et al., 2012, Maizlish et al., 2013, Woodcock et al., 2009, Woodcock et al., 2013), the proportional change in incidence of non-fatal injuries was used to estimate the change in YLDs due to traffic injuries from baseline levels and the change in incidence of fatal injuries was used to estimate the change in YLLs . Rojas-Rueda et al. (2013) calculated the increase in YLDs due to non-fatal injuries by assuming for avoided minor injuries, a disability duration and severity weight equal to that of a sprain diagnosis which were obtained from a previous study. For major injuries, an average duration and severity weight of severe injuries was assumed. Dhondt et al. (2013) took a more complex approach. For each predicted fatal injury, a specific age was sampled stochastically from within the broader age strata being used for the analysis and life-table analysis with age-specific mortality rates was employed to calculate the YLLs. For each predicted non-fatal injury, first an injury diagnosis was sampled stochastically from injury distributions derived from national hospital data. Then an injury specific disability weight was assigned using values from a previous study (Haagsma et al., 2012). For temporary injuries, a duration of 1 year was assigned and for long term injuries, the duration was assumed to be the remaining life expectancy.

6. Results

In this section, some trends which can be found in the results of these studies are discussed. In some studies such as (Dhondt et al., 2013) and (Grabow et al., 2012), was unclear how much of the resulting impacts could be attributed to increases in walking and cycling. However, in the remaining studies, although the scenarios under study were different, some interesting commonalities and differences could be found. Firstly, the total benefits of active travel outweighed the risks in all studies. However, (Woodcock et al., 2014) found that the benefits for females were much lower than males and that under certain modelling assumptions, there was no evidence of a benefit to women. This was partially due to the lower age distribution and baseline disease rate of women in this study as well as their higher background rate of fatal injuries from heavy goods vehicles. In almost all studies where several determinants of health related to active travel were considered, physical activity was the most important, in most cases by a substantial margin. Traffic collisions were the next most significant determinant, particularly in studies which included non-fatal traffic injuries in addition to fatalities. Some studies (Macmillan et al., 2014, Rabl and de Nazelle, 2012, Rojas-Rueda et al., 2013) even found that the change in cost of non-fatal collisions was more significant than the change in cost of fatal collisions. Although, in most cases, the cost of traffic collisions increased as a result of the increase in active travel, studies which considered the collision risk of motorized modes and the “Safety in Numbers” effect yielded significantly more optimistic results than those which maintained the current injury rates for each mode. (Woodcock et al., 2013) even found a reduction in the BOD due to traffic collisions in the increased active travel scenario. This was the only study to incorporate changes to freight and changes in travel distance in the more active scenario in their traffic collision model. (Woodcock et al., 2009) found that the burden of road traffic injury increased for London but decreased for Delhi in the active travel scenarios, but it was noted that this difference in direction may indicate uncertainty. (Holm et al., 2012) on the other hand, found the increase in health burden from traffic collisions to be comparable to the decrease in health burden due to physical activity. In all studies, the health impacts of changes in external

pollution were positive but relatively small and the health impacts of in-travel exposures to air pollution were negative and almost negligible.

7. Conclusion

There are significant differences in the steps taken by the studies reviewed to assess the health impact of active travel and these differences in methodologies can have a considerable impact on the results. Physical activity is by far the most important determinant of net benefits and different models for assessing this impact can produce vastly different results using the same data. Further research is required in order to reach a consensus on the most suitable model. Some of the studies in this review only considered the negative impacts of air pollution and traffic collisions which were specific to those travellers who switched modes and ignored the reductions in external pollution costs and collision risks to other travellers. It is recommended that, wherever possible, both the individual and societal impacts of each determinant of health are considered in order to avoid bias. The summary health measure used as the outcome variable should be chosen carefully. Using BOD as the outcome variable may be expected to provide a more comprehensive evaluation of health impacts due to the inclusion of morbidity in addition to mortality. However, using BOD may produce more conservative results than mortality if the range of diseases considered is not comprehensive enough. For example, (Rojas-Rueda et al., 2013) did not consider depression as an outcome but the studies of Woodcock and colleagues found significant increases in the BOD due to depression. The method by which health impacts are monetised is also an important consideration. Studies which used a static mortality approach may have overestimated the economic value of active travel by using VSL to monetise the change in mortality, rather than VOLY which is a more suitable measure of the value of a change in mortality resulting from chronic health effects.

The importance of sensitivity analysis in Health Impact Analyses of active travel must be emphasised. These studies rely heavily on relationships modelled by previous studies and there are both uncertainties inherent in these models and disagreement between different models. This is particularly important in estimating the health impacts of increased physical activity as they tend to dominate the overall results.

This review has identified several methodological challenges and areas for future research. Studies which quantify health impacts of active travel are highly dependent on reliable data relating to current transport environments and, in particular, pollution exposure and traffic collisions. All of the studies which considered in-travel pollution exposures found the impact to be small but most studies were based on data from fixed monitoring stations which often have little correlation with the personal exposure of commuters. There is a need for more studies which measure this exposure directly. Efforts should also be directed towards identifying methods of correcting collision data for inaccuracies, particularly with regard to underreporting of collisions in active modes. One European study has suggested that non-fatal bicycle injuries are underreported by more than a factor of five (Bickel et al., 2006) and yet, few of the studies in this review accounted for potential underreporting of traffic collisions.

Almost all of the studies reviewed focussed on evaluating the health impacts resulting from a modal shift but did not attempt to simulate the pathways which lead to model shift. This presents an opportunity to build on this work and increase the applicability of such studies to transport planning and policy formulation, through further research into the integration of these methods with travel demand forecasting models. Two of the studies integrated activity based modelling into their models. However, although activity based approaches are frequently used in academic settings, four stage transport models are more commonly used in practical travel forecasting applications. Integration of a health impact model with a four stage transport model would be an ideal way of

incorporating health impacts into policy formulation and infrastructure planning processes and bridging this area of research with practice. Future research should also focus on identifying the causes for the large discrepancies between the results of different models of the health impacts of physical activity. Physical activity has been consistently shown to be the most significant determinant of the health impacts of increased active travel but the magnitude of the impact is still difficult to quantify due to wide variations in the results of different models. A consensus on the best approach would increase the credibility and policy relevance of these studies.

Acknowledgement

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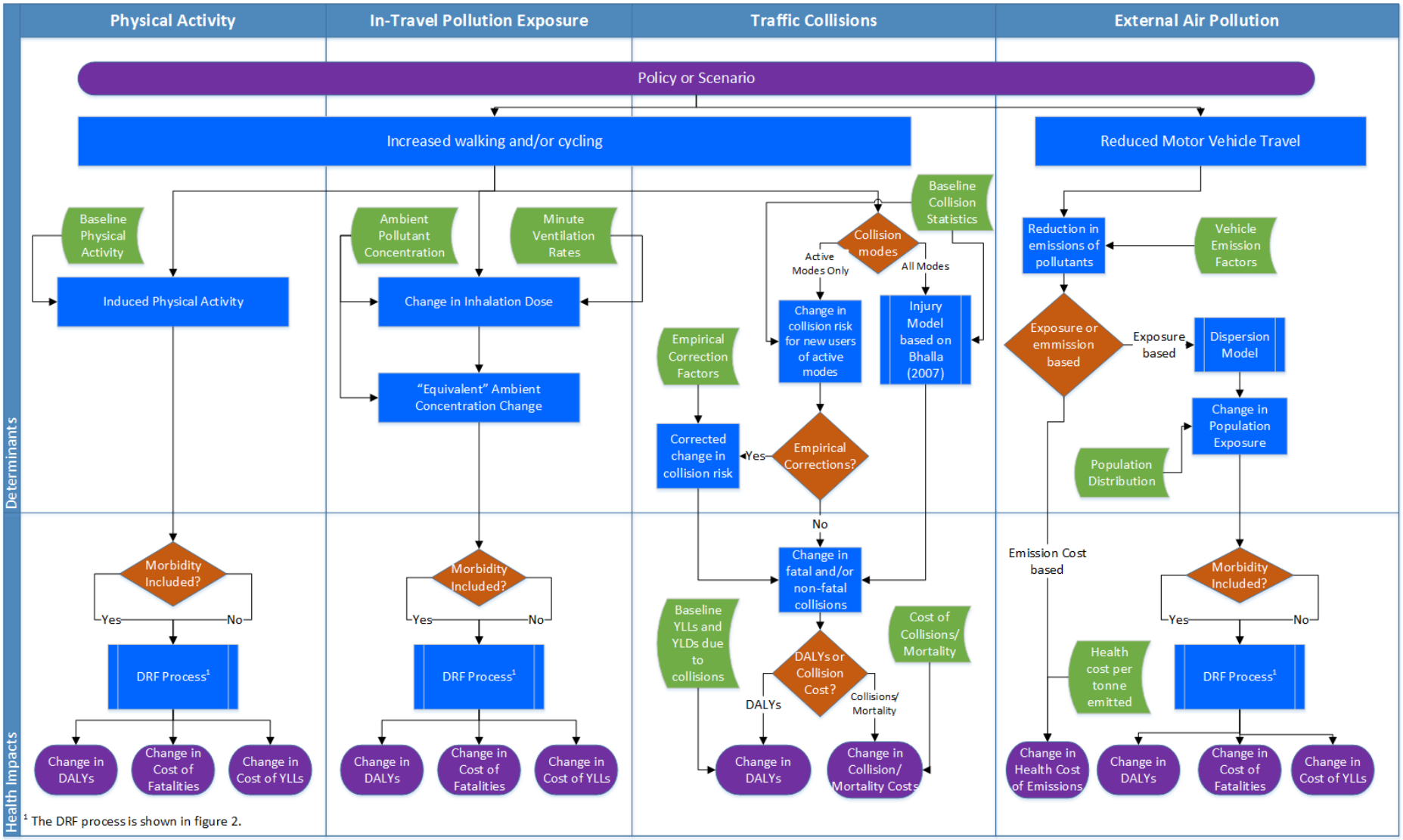

Figure 1. Process Flow for Quantification of the Health Impacts of Active Travel.

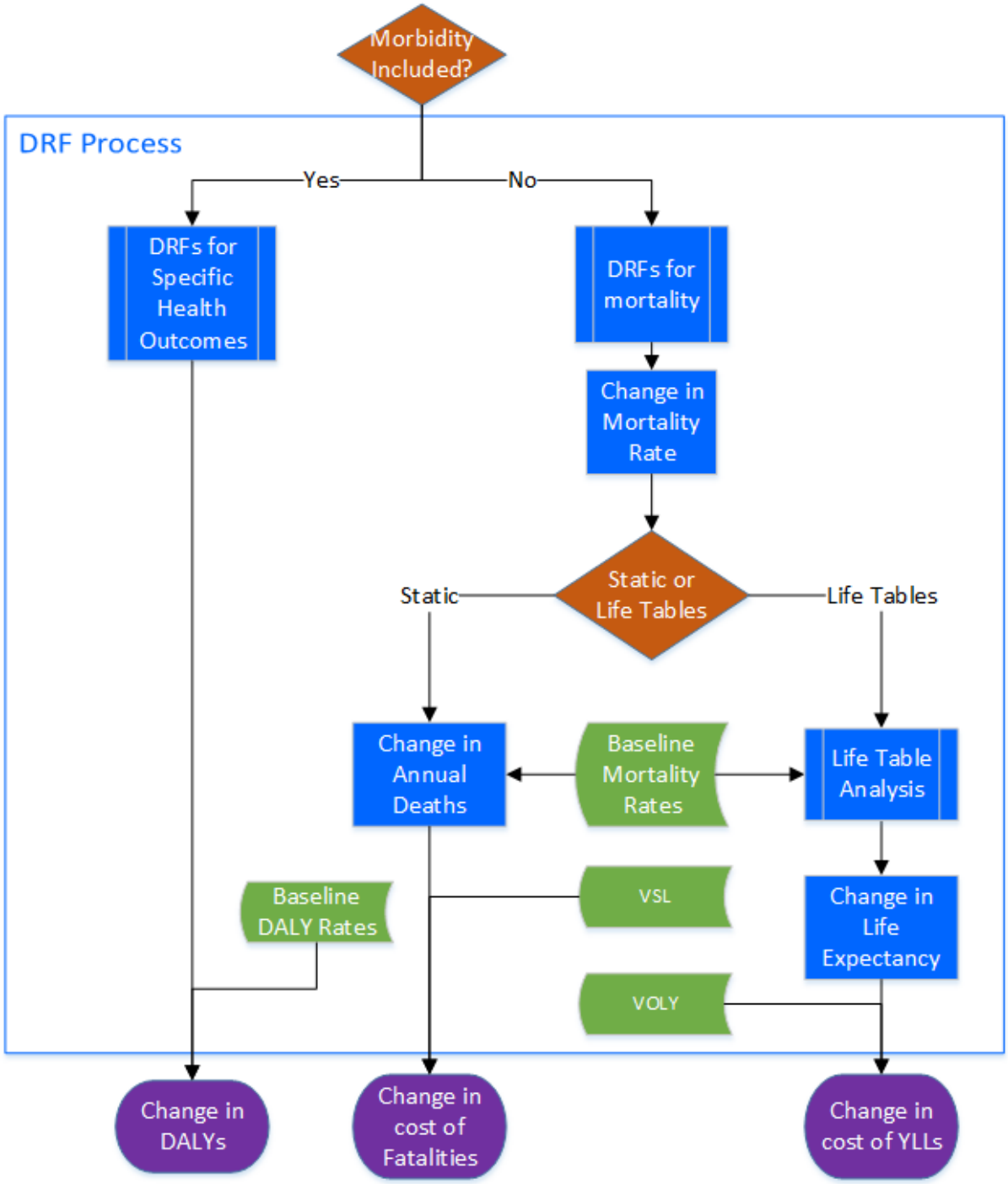

Figure 2. DRF Process Flow

Table 1

Summary of studies reviewed

Author(s)	Year	Scenario	Study Location	Active modes
de Nazelle et al.	2009	Hypothetical built enviorment transformation	Orange County, NC, USA	Walking
Woodcock et al.	2009	Hypothetical transportation strategies to reduce greenhouse gas emissions (GHGE).	London, UK	Walking
Gotschi et al.	2011	Three hypothetical transport scenarios involving higher modal shares of cycling	Portland, Oregon	Cycling
Grabow et al.	2011	Hypothetical elimination of short automobile trips and replacement of 50% with cycling.	Upper midwestern USA	Cycling
Hartog et al.	2011	Hypothetical transition from car driving to cycling for 500,000 people for short daily trips	Netherlands	Cycling
Lindsay et al.	2011	Hypothetical transition from car driving to cycling for short trips	Urban areas in New Zealand	Cycling
Rojas-Rueda et al.	2011	Assessment of existing bicycle hire scheme	Barcelona, Spain	Cycling
Fishman et al.	2012	Assessment of existing bicycle hire scheme	Barcelona, Spain	Cycling
Holm et al.	2012	Hypothetical transition from car driving to cycling for trips to place of work or education on weekdays	Copenhagen, Denmark	Cycling
Rabl and de Nazelle	2012	Hypothetical transition from car driving to walking or cycling for commuting to and/or from work.	Generalisable	Walking Cycling
Rojas-Rueda et al.	2012	Eight hypothetical transport scenarios involving replacement of car trips by active travel and public transport	Barcelona, Spain	Walking Cycling
Dhondt et al.	2013	Hypothetical increase in fuel price	Flanders and Brussels, Belgium	Walking Cycling
Maizlish et al.	2013	Three hypothetical transportation strategies to reduce greenhouse gas emissions (GHGE).	San Francisco Bay	Walking
Olabarria et al.	2013	Hypothetical scenario where people not meeting physical activity guidelines convert walkable driving trips to walking.	Catalonia, Spain	Walking
Rojas-Rueda et al.	2013	8 hypothetical transport scenarios involving replacement of car trips by active travel and public transport	Barcelona, Spain	Walking Cycling
Woodcock et al.	2013	3 hypothetical scenarios descibed by the Visions 2030 project involving increased levels of walking, cycling, public transport and electric vehicle use.	Urban areas in England and Wales outside of London	Walking Cycling
Deenihan et al.	2014	Hypothetical increase in cycling share due to construction of a segregated cycleway.	Leinster, Ireland	Cycling
Macmillan et al.	2014	5 hypothetical policy scenarios over the next 40 years.	Aukland, New Zealand	Cycling
Woodcock et al.	2014	Assessment of existing bicycle hire scheme	London, UK	Cycling

Table 2

Summary of health summary measures considered and monetisation in studies reviewed

Author(s)	Year	Health Summary	Unit of Measurement	Monetisation
de Nazelle et al.	2009	-	-	-
Woodcock et al.	2009	Disease-specific BOD	Deaths YLL YLD DALYs	VSL
Gotschi et al.	2011	All-Cause Mortality Cost of illness	Deaths Health care costs	VSL
Grabow et al.	2011	All-Cause Mortality Disease-Specific Morbidity	Deaths Disease Incidence ER Visits School-loss days Work-loss days Worker Productivity	VSL "Damage Function" (BenMAP)
Hartog et al.	2011	All-Cause Mortality	YLLs	-
Lindsay et al.	2011	Mortality Morbidity Health Care Costs Energy Expenditure	Deaths Restricted Activity Days Hospital Admissions kJ expended over baseline MET rate	VSL Cost per Health Event (HAPiNZ)
Rojas-Rueda et al.	2011	All-Cause Mortality	Deaths	-
Fishman	2012	Mortality Morbidity	Not Stated	Value per km of cycling Value per km of walking
Holm et al.	2012	Disease-specific BOD	DALYs	-
Rabl and de Nazelle	2012	All-Cause Mortality	Deaths YLLs	VSL VOLY
Rojas-Rueda et al.	2012	All-Cause Mortality	Deaths YLLs	-
Dhondt et al.	2013	Mortality Morbidity	YLLs YLDs DALYs	-
Maizlish et al.	2013	Disease-specific BOD	DALYs	-
Olabarria et al.	2013	All-Cause Mortality	Deaths	VSL
Rojas-Rueda et al.	2013	Disease-specific BOD	DALYs	-
Woodcock et al.	2013	Disease-specific BOD All-Cause Mortality	DALYs Deaths	-
Deenihan et al.	2014	Mortality	Deaths	VSL
Macmillan et al.	2014	Mortality Morbidity Health Care Costs	Deaths Injuries Restricted Activity Days Hospital Admissions	Cost of bicycling fatal injury (NZTA) Cost of pollution mortality (HAPiNZ) Cost of cycling serious injury (NZTA) Restricted Activity Days (HAPiNZ) Hospitalisation Costs (HAPiNZ)
Woodcock et al.	2014	Disease-specific BOD All-Cause Mortality	DALYs YLLs	-

Table 3
Summary of physical activity effects considered in studies reviewed

Author(s)	Year	Unit of Measurement	Exposure-Response Relationship
de Nazelle et al.	2009	Daily energy expenditure	Proportion of days exceeding USDHHS (1996) energy expenditure thresholds
Woodcock et al.	2009	Physical Activity MET hours	Various published RRs of specific diseases for physical activity.
Gotschi et al.	2011	Time spent cycling	HEAT for cycling Assumed health care cost attributable to inactivity is proportional to number of inactive people
Grabow et al .	2011	Average distance cycled	HEAT for cycling
Hartog et al.	2011	Distance cycled	Range of RRs of mortality for cycling (0.5-0.90) based on published values
Lindsay et al.	2011	Average distance cycled	HEAT for cycling
Rojas-Rueda et al.	2011	Average distance cycled	HEAT for cycling
Fishman et al.	2012	Additional distance cycled Reduction in distance walked	Values per km walked/cycled from New Zealand Transport Agency (2010, Vol. 2)
Holm et al.	2012	Total time in physical activity, categorised as sufficiently active, moderately active or inactive.	RRs of specific diseases between the physical activity categories from the WHO's Comparative Quantification of Health Risks study
Rabl & de Nazelle	2012	Time spent cycling	Andersen RR of mortality for cycling with USDHHS (2008) DRF
Rojas-Rueda et al.	2012	Average distance cycled Average distance walked	HEAT for cycling HEAT for walking
Dhondht et al.	2013	Physical Activity MET hours	RR of mortality for moderate physical activity from Woodcock (2011)
Maizlish et al.	2013	Physical Activity MET hours	Various published RRs of specific diseases for physical activity.
Olabarria et al.	2013	Time spent in new walking	HEAT for walking
Rojas-Rueda et al.	2013	Average distance cycled Average distance walked	Various published RRs of specific diseases for physical activity.
Woodcock et al.	2013	Physical Activity MET hours	Various published RRs of specific diseases for physical activity. RRs of all-cause mortality for walking and total physical activity from Woodcock (2011) RRs of all-cause mortality from Andersen (2000) HEAT for walking HEAT for cycling
Deenihan et al.	2014	Average distance cycled	HEAT for cycling
Macmillan et al.	2014	Cycling distance range	Assumed RR of mortality for cycling based on Andersen (2000) and Matthews (2007) with linear dose response vs range of commuter cycling where <=6 km corresponds to the reference RR.
Woodcock et al.	2014	Physical Activity marginal MET hours	Various published RRs of specific diseases for physical activity. RRs of all-cause mortality for walking and total physical activity from Woodcock (2011). RRs of mortality for physical activity categories from Wen CP (2011); fitting linear relationships to connect categories of MET hours per week.

Table 4

Summary of pollution effects considered in studies reviewed

		In-travel exposure		External exposure	
Author(s)	Year	Pollutant	Health Effects	Pollutant	Health Effects
de Nazelle et al.	2009	PM10 O_3	Proportion of days exceeding NAAQS thresholds	-	-
Woodcock et al.	2009	-	-	PM2.5	RR of specific diseases from Ostro, 2004#
Gotschi et al.	2011		-	-	-
Grabow et al .	2011	-	-	PM2.5 O_3	Concentration response functions for PM2.5 from US EPA 2006 Regulatory Impact Analysis Exposure response functions for O_3 from NAAQS
Hartog et al.	2011	PM2.5 BS	RR of mortality for PM2.5 from Pope, 2002 # RR of mortality for BS from Beelen, 2008 #	NO_2 PM10	RR of mortality from Tonne et al., 2008#
Lindsay et al.	2011	-	-	PM10 CO Benzene	Assumed impacts of air pollution estimated by HAPiNZ were proportional to vehicles kilometers travelled per square km
Rojas-Rueda et al.	2011	PM2.5	RR of mortality from Krewski 2009#	-	-
Fishman et al.	2012				
Holm et al.	2012	PM2.5	RR of spcific diseases for PM2.5 from Pope, 2002 #	-	-
Rabl and de Nazelle	2012	PM2.5	RR of mortality from Pope, 2002#	PM2.5	RR of mortality from Pope, 2002#
Rojas-Rueda et al.	2012	PM2.5	RR of mortality from Krewski, 2009#	PM2.5	RR of mortality from Krewski, 2009#
Dhondt et al.	2013	EC	RR of mortality from Janssen et al 2011# RRs of CVD hospital admissions from Tolbert et al., 2007 #and Peng et al., 2009#	EC	RR of mortality from Janssen et al 2011# RRs of CVD hospital admissions from Tolbert et al., 2007 #and Peng et al., 2009#
Maizlish et al.	2013	-	-	PM2.5	RR of specific diseases from Ostro, 2004#
Olabarria et al.	2013	-	-	-	-
Rojas-Rueda et al.	2013	PM2.5	RR of various diseases	PM2.5	RR of various diseases
Woodcock et al.	2013	-	-	PM2.5	RR of specific diseases from Ostro, 2004#
Deenihan et al.	2014	-	-	-	-
Macmillan et al.	2014	-	-	PM10 CO	Modelled health outomes based on changes in light vehicle emissions and population using HAPiNZ Health Effects Model.
Woodcock et al.	2014		RRs of specific diseases from Ostro, B. 2004#	-	-

Table 5

Summary of road traffic collision analysis in studies reviewed

Author(s)	Year	Travellers changing mode	Other travellers
de Nazelle et al.	2009	-	-
Woodcock et al.	2009	✓	✓
Gotschi et al.	2011	-	-
Grabow et al.	2011	-	-
Hartog et al.	2011	✓	✓
Lindsay et al.	2011	✓	✓
Rojas-Rueda et al.	2011	✓	-
Fishman et al.	2012		
Holm et al.	2012	✓	-
Rabl and de Nazelle	2012	✓	✓
Rojas-Rueda et al.	2012	✓	-
Dhondt et al.	2013	✓	✓
Maizlish et al.	2013	✓	✓
Olabarria et al.	2013	-	-
Rojas-Rueda et al.	2013	✓	-
Woodcock et al.	2013	✓	✓
Deenihan et al.	2014	-	-
Macmillan et al.	2014	✓	-
Woodcock et al.	2014	✓	✓

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