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Determination of active travel speed for minimum air pollution inhalation

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ABSTRACT

A higher active travel speed has offsetting impacts on air pollution inhalation dose through higher breathing rate but shorter exposure duration. The net effect of speed choice on inhalation dose for pedestrians and bicyclists has not been established. This paper derives equations for pedestrian and bicycle steady-state minimum-dose speed (MDS). Parameter distributions from the literature are applied to a synthetic population of travelers to calculate individual MDS. Results strongly support the existence of a definable MDS, which is near observed travel speeds for urban pedestrians and bicyclists. For a wide range of travelers, the MDS is 2–6 km/h while walking and 12–20 km/h while bicycling, decreasing with road grade at a rate similar to observed speeds. On level ground, pedestrian and bicycle MDS corresponds to a moderate-intensity physical activity level (3–6 MET). Small deviations from the MDS have little effect, but large deviations (by more than 10 km/h for bicycling) can more than double inhalation dose over a fixed distance. It appears that pedestrians and bicyclists choose travel speeds that approximately minimize pollution inhalation dose, although pollution is unlikely a primary motivation.

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1. Introduction

Human exposure to traffic-related air pollution in cities is a significant public health problem (Health Effects Institute, 2010). Disproportionately high doses of several pollutants are inhaled during travel due to high concentrations around roadways (Dons, Int Panis, Van Poppel, Theunis, & Wets, 2012; Fruin, Westerdahl, Sax, Sioutas, & Fine, 2008). Inhalation doses for active travelers (pedestrians and bicyclists) are especially high because of high breathing rates (Bigazzi & Figliozzi, 2014; de Nazelle et al., 2012). In addition to the objective risk, air pollution exposure is an expressed concern for travelers and a barrier to active travel for some (Badland & Duncan, 2009).

Ventilation rate ($\dot{V}_E$) during active travel is influenced by energy expenditure (often expressed as the rate of metabolic oxygen consumption, $\dot{V}O_2$), which, in turn, is influenced by the travel speed (v), roadway environment (road grade, surface, etc.), and other factors such as baggage and equipment mass, tire pressure, and riding position. A higher v has offsetting effects on inhalation dose, leading to higher $\dot{V}_E$ but shorter exposure duration.

As early as the 1950s, researchers calculated the walking speed to minimize energy expenditure per unit travel distance (Ralston, 1958; van der Walt & Wyndham, 1973). Those results do not directly apply to air pollution inhalation because $\dot{V}_E$ is not proportional to $\dot{V}O_2$ across all activity intensities (McArdle, Katch, & Katch, 2010; West, 2012). The relationship between $\dot{V}_E$ and v is expected to be nonlinear because 1) $\dot{V}O_2$ increases nonlinearly with speed for both walking and bicycling (Kramer, 2010; Olds, 2001) and because 2) the relationship between $\dot{V}_E$ and $\dot{V}O_2$ is nonlinear. To the author's knowledge, no study has yet examined the effect of speed on inhalation dose for active travelers while accounting for these nonlinearities.

The main objective of this paper is to determine the pedestrian and bicycle steady-state travel speeds that minimize air pollution inhalation dose per unit distance. Comparing observed active travel speeds with minimum-dose speeds (MDSs) can provide insights into potential dose reductions through speed moderation and allow an examination of trade-offs among travel time, physical activity, and pollution dose arising from travel speed choice. Equations for determining MDSs are derived from previously established models of human ventilation and energy expenditure. Parameter distributions are applied to calculate the MDS at varying road grades for a synthetic population. The effects of travel dynamics (stops and accelerations) and ground-level wind are left for future work.

2. Methods

2.1 *Derivation of the minimum-dose speed*

Steady-state pollution inhalation dose rate per unit distance $\dot{I}_d$ can be expressed as a function of pollutant concentration in breathing zone air C, ventilation rate $\dot{V}_E$, and travel speed v,

$$\dot{I}_d = \frac{1}{6\times10^4}\frac{C\dot{V}_E}{v} \tag{1}$$

with $\dot{I}_d$ in μg/m, v in m/s, C in μg/m^3, and $\dot{V}_E$ in l/min. The objective of this paper is to determine the MDS: the value of

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$v > 0$ at which $\dot{I}_d$ is minimized. We assume for this analysis of active travelers that concentration is independent of speed, $\frac{dC}{dv} = 0$, ventilation increases with speed, $\frac{d\dot{V}_E}{dv} > 0$, and there is a positive resting ventilation rate, $\dot{V}_E > 0$ at $v = 0$.

The behavior of $\dot{I}_d$ at the lower and upper extremes of the v range $(0, \infty)$ is

$$\lim_{v \to 0} \dot{I}_d = \infty$$

and

$$\lim_{v \to \infty} \dot{I}_d = \lim_{v \to \infty} \frac{C}{6 \times 10^4} \frac{d\dot{V}_E}{dv}.$$

If $\lim_{v \to \infty} \dot{I}_d = 0$, then there is no finite MDS—increasing speed always reduces inhalation dose over a fixed distance. Similarly, if $\dot{V}_E$ is a linear function of v, then $\lim_{v \to \infty} \dot{I}_d$ is a finite positive number approached asymptotically from above, and there is no finite MDS. If, however, $\lim_{v \to \infty} \frac{d\dot{V}_E}{dv} = \infty$, then $\dot{I}_d$ approaches ∞ at both end points of the speed range $(0, \infty)$, and there must be a finite MDS. Assuming $\dot{I}_d$ is a continuous twice-differentiable function of v over $(0, \infty)$, the MDS would be at a real solution of $\frac{d\dot{I}_d}{dv} = 0$ where $\frac{d^2\dot{I}_d}{dv^2} > 0$ (i.e., the MDS must be at a local minimum).

From Equation (1), $\dot{I}_d$ is a continuous differentiable function of v over $(0, \infty)$ if $\dot{V}_E$ is a continuous differentiable function of v:

$$\frac{d\dot{I}_d}{dv} = \frac{1}{6 \times 10^4} \frac{C}{v} \left(\frac{d\dot{V}_E}{dv} - \frac{\dot{V}_E}{v} \right) \tag{2}$$

and

$$\frac{d^2\dot{I}_d}{dv^2} = \frac{1}{6 \times 10^4} \frac{C}{v} \left[\frac{d^2\dot{V}_E}{dv^2} - \frac{2}{v} \frac{d\dot{V}_E}{dv} + 2 \frac{\dot{V}_E}{v^2} \right]. \tag{3}$$

From Equation (2), finite critical values of v (where $\frac{d\dot{I}_d}{dv} = 0$) must satisfy

$$\frac{d\dot{V}_E}{dv} = \frac{\dot{V}_E}{v}. \tag{4}$$

Substituting Equation (4) into (3), $\frac{d^2\dot{I}_d}{dv^2} > 0$ is also satisfied at critical values of v if $\frac{d^2\dot{V}_E}{dv^2} > 0$. If $\frac{d^2\dot{V}_E}{dv^2} > 0$ over $v > 0$ (i.e., $\dot{V}_E$ is a strictly convex function of v), there is at most one critical value, which is at the absolute minimum (i.e., the MDS). Summarizing, a finite MDS exists if $\lim_{v \to \infty} \frac{d\dot{V}_E}{dv} = \infty$, and the MDS can be found by solving for $v > 0$ that satisfies Equation (4), on the condition that $\dot{V}_E$ is a strictly convex function of v over $v > 0$. The next step to calculate the MDS is to determine the relationship, $\dot{V}_E = f(v)$.

2.2 *Ventilation as a function of speed*

The relationship between $\dot{V}_E$ and v is derived from previously developed functional models of $\dot{V}_E$, energy expenditure ($\dot{V}O_2$ in l O_2/min), and human external power output (P in watts). As illustrated in Figure 1, $\dot{V}_E$ can be expressed as a function of $\dot{V}O_2$ or P (A and C in the figure); $\dot{V}O_2$, in turn, can be expressed as a function of P or v (B and E in the figure); P during bicycling can be expressed as a function of v (D in the figure). Other intermediate relationships are not relevant or not common in the literature (e.g., P during level walking is nearly zero). $\dot{V}_E = f(v)$ is derived from the functional combinations (paths in Figure 1): ABD (bicycle), CD (bicycle), and AE (pedestrian). For example, path ABD would lead to $\dot{V}_E = f(\dot{V}O_2(P(v)))$. Functional forms for A through E are discussed in the remainder of this section.

The relationship between $\dot{V}_E$ and $\dot{V}O_2$ (A in Figure 1) has been modeled as linear (McArdle et al., 2010; Newstead, 1987), log-linear (Baba, Kubo, Morotome, & Iwagaki, 1999; Baba et al., 1996; Hollenberg & Tager, 2000; Zoladz, Rademaker, & Sargeant, 1995), and log-log (U.S. Environmental Protection Agency, 2009). The linear relationship only pertains to a limited range of $\dot{V}O_2$; the $\dot{V}_E / \dot{V}O_2$ ratio (or ventilatory equivalent) increases for $\dot{V}O_2$ above the anaerobic or ventilatory threshold, around 2 l O_2/min (Layton, 1993; McArdle et al., 2010; West, 2012). All three formulations of $\dot{V}_E = f(\dot{V}O_2)$ are explored in this analysis with parameters α_x and β_x where x is the functional form, $x \in \{\text{lin}, \text{loglin}, \text{log}\}$,

- Model A_{lin}: $\dot{V}_E = \alpha_{\text{lin}} + \beta_{\text{lin}} \dot{V}O_2$;
- Model A_{loglin}: $\ln\dot{V}_E = \alpha_{\text{loglin}} + \beta_{\text{loglin}} \dot{V}O_2$;
- Model A_{log}: $\ln\dot{V}_E = \alpha_{\text{log}} + \beta_{\text{log}} \ln\dot{V}O_2$.

Bicycling $\dot{V}O_2$ is a linear function of P (B in Figure 1), where δ_0 is the energy expenditure of unloaded bicycling [around twice the resting metabolic rate (RMR)] and δ_1 is a parameter representing human mechanical efficiency (Glass, Dwyer, & American College of Sports Medicine, 2007):

- Model B: $\dot{V}O_2 = \delta_0 + \delta_1 P$.

In addition, $\dot{V}_E$ during urban bicycling has been directly estimated from P (C in Figure 1) as

- Model C: $\ln\dot{V}_E = \gamma_0 + \gamma_1 P$.

where γ_0 and γ_1 are empirical parameters (Bigazzi & Figliozzi, 2015). Bicycling P can be calculated from steady-state v (D in Figure 1) using well-validated physical models (Martin, Milliken, Cobb, McFadden, & Coggan, 1998;

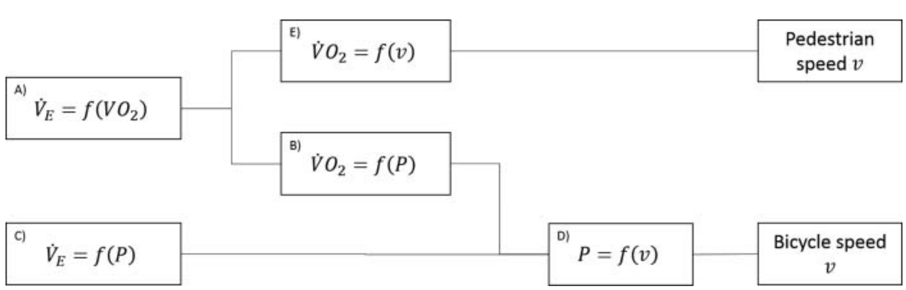

Figure 1. Framework for deriving ventilation-speed function.

Table 1. Ventilation as a function of speed and resulting equations for MDS.

Model	Mode	$\dot{V}_E = f(v)$[1]	MDS equations[2]
$A_{lin}BD$	Bicycle	$\alpha_{lin} + \beta_{lin}(\delta_0 + \delta_1(\mu_1 v + \mu_3 v^3))$	$2\delta_1\mu_3 v^3 - \left(\delta_0 + \frac{\alpha_{lin}}{\beta_{lin}}\right) = 0$
$A_{loglin}BD$	Bicycle	$\exp\left(\alpha_{loglin} + \beta_{loglin}(\delta_0 + \delta_1(\mu_1 v + \mu_3 v^3))\right)$	$3\mu_3 v^3 + \mu_1 v - \frac{1}{\delta_1 \beta_{loglin}} = 0$
$A_{log}BD$	Bicycle	$\exp\left(\alpha_{log} + \beta_{log}\ln(\delta_0 + \delta_1(\mu_1 v + \mu_3 v^3))\right)$	$(3\beta_{log} - 1)\mu_3 v^3 + (\beta_{log} - 1)\mu_1 v - \frac{\delta_0}{\delta_1} = 0$
CD	Bicycle	$\exp(\gamma_0 + \gamma_1(\mu_1 v + \mu_3 v^3))$	$3\mu_3 v^3 + \mu_1 v - \frac{1}{\gamma_1} = 0$
$A_{lin}E$	Pedestrian	$\alpha_{lin} + \beta_{lin}(\theta_0 + \theta_1 v + \theta_2 v^2)$	$\theta_2 v^2 - \left(\theta_0 + \frac{\alpha_{lin}}{\beta_{lin}}\right) = 0$
$A_{loglin}E$	Pedestrian	$\exp\left(\alpha_{loglin} + \beta_{loglin}(\theta_0 + \theta_1 v + \theta_2 v^2)\right)$	$2\theta_2 v^2 + \theta_1 v - \frac{1}{\beta_{loglin}} = 0$
$A_{log}E$	Pedestrian	$\exp\left(\alpha_{log} + \beta_{log}\ln(\theta_0 + \theta_1 v + \theta_2 v^2)\right)$	$(2\beta_{log} - 1)\theta_2 v^2 + (\beta_{log} - 1)\theta_1 v - \theta_0 = 0$

[1]Speed range: $v^2 \geq \frac{-\mu_1}{\mu_3}$ for bicycle and $v > 0$ for pedestrian.
[2]From application of $\dot{V}_E = f(v)$ to Equation 4; MDS is solution value of v within the speed range.

Olds, 2001; Wilson, 2004): $P = \max\left(\mu_1 v + \mu_3 v^3, 0\right)$ where μ_1 and μ_3 are parameters representing rolling resistance and aerodynamic drag (discussed in section 2.3). This equation is simplified to

- Model D: $P = \mu_1 v + \mu_3 v^3$

for $v^2 \geq \dfrac{-\mu_1}{\mu_3}$ in order to define a differentiable function for $\dot{V}_E$. Pedestrian $\dot{V}O_2$ is commonly modeled as a quadratic function of v (E in Figure 1),

- Model E: $\dot{V}O_2 = \theta_0 + \theta_1 v + \theta_2 v^2$

where θ_i are parameters that can depend on travel and traveler characteristics such as body mass, road grade, RMR, and sex (Brooks, Gunn, Withers, Gore, & Plummer, 2005; Kramer, 2010; Pimental & Pandolf, 1979).

Including the three forms of model A, seven functional forms for $\dot{V}_E = f(v)$ are derived from models A through E, as shown in Table 1. The valid speed ranges for the pedestrian and bicycle models, respectively, are $v = 0$ and $v^2 \geq \frac{-\mu_1}{\mu_3}$. Corresponding expressions for $\frac{d\dot{V}_E}{dv}$ and $\frac{d^2\dot{V}_E}{dv^2}$ are given in the Supplemental Material, Table S1. The last column in Table 1 gives MDS equations, the result of applying each $\dot{V}_E = f(v)$ to Equation (4) and rearranging to a polynomial of v. The bicycle MDS equations are cubic (due to the third-order aerodynamic drag term in model *D*), while the pedestrian MDS equations are quadratic (due to the form of model *E*).

All $\dot{V}_E = f(v)$ in Table 1 are continuous and twice differentiable over their speed range. In addition, if the parameters $\{\beta_x, \delta_1, \gamma_1, \mu_3, \theta_2\}$ are positive and $\beta_{log} > 1$, all of which are expected (see the next section on parameter values), it can be shown that $\lim_{v\to\infty} \frac{d\dot{V}_E}{dv} = \infty$ and $\frac{d^2\dot{V}_E}{dv^2} > 0$. Thus, a finite MDS exists and can be found by solving the MDS equations in the last column of Table 1 for v. Exactly one positive solution to each MDS equation can be confirmed by Descartes' Rule of Signs (using the assumption $\dot{V}_E > 0$ at $v = 0$, in addition to the preceding parameter constraints). For the bicycle models, if the solution to the MDS equations is in the range $(0, \sqrt{\frac{-\mu_1}{\mu_3}})$, then the MDS is at the lower end point, $v = \sqrt{-\mu_1/\mu_3}$ (implying $P = 0$).

2.3 *Parameter estimates*

Parameter distributions are used to calculate MDS for a broad variety of travelers. Age and body mass for a synthetic population of 10,000 persons, half male and half female, are sampled from the distributions in 2012 US population census data (US Census Bureau, 2013). RMR, which is needed for δ_0 and θ_i, is calculated from equations for basal metabolic rate as a function of age, sex, and body mass (Schofield, 1985). Metabolic rate is converted to the units of $\dot{V}O_2$ (l O_2/min) using an individual oxygen conversion efficiency H (in l O_2 per kcal) sampled from uniform distributions of 0.19–0.20 for females and 0.20–0.22 for males (U.S. Environmental Protection Agency, 2009).

For model A_{lin}, $\alpha_{lin} = 0$ and β_{lin} is sampled from a lognormal distribution with a mean of 27 and geometric standard distribution of 1.18 (Layton, 1993). For model A_{loglin}, β_{loglin} is calculated from oxygen uptake efficiency slope (OUES) as $\beta_{loglin} = \frac{\ln 10}{OUES}$; OUES is sampled from a normal distribution with a mean of 2.55 and standard deviation of 1.01 (Sun, Hansen, & Stringer, 2012), truncated at two standard deviations from the mean. Low values of β_{loglin} are expected for fit individuals, and high values are expected for children and persons with heart or respiratory diseases or obesity (Baba et al., 1999; Drinkard et al., 2007; Hollenberg & Tager, 2000; Marinov & Kostianev, 2003; Van Laethem et al., 2005; Williamson et al., 2012). For model A_{log}, β_{log} is taken from age-specific values ranging from 1.04 to 1.17 (U.S. Environmental Protection Agency, 2009). α_{loglin} and α_{log} are not needed to calculate the MDS but can be taken from the same references.

For model B, δ_0 and δ_1 are sampled from normal distributions with mean values taken from American College of Sports Medicine equations for leg bicycling at 50–200 W (Glass et al., 2007): $\delta_0 = 2 \cdot RMR$ and $\delta_1 = 0.011$ (implying a human delta efficiency of 26%), and standard deviations based on a coefficient of variation of 7% (Moseley & Jeukendrup, 2001). For model C, γ_1 is sampled from a normal distribution with a mean of 0.00645 and standard deviation of 0.002, truncated at two standard deviations, based on the pooled model by Bigazzi & Figliozzi (2015). For model D, the first-order bicycle power coefficient is $\mu_1 = (m + m_b)g(G + C_R)$ with the rider mass m in kg, bicycle mass m_b in kg, gravitation constant $g = 9.8$ m/s^2, road grade G (unitless), and coefficient of rolling resistance C_R (unitless). The third-order coefficient $\mu_3 = 0.5\rho C_D A_F$, with the air density $\rho = 1.23$ kg/m^3, drag coefficient C_D (unitless), and frontal area A_F in m^2. C_R, A_F, and C_D are sampled from normal distributions with means of 0.004, 0.6, and 1.0, and standard deviations of 0.001, 0.1, and 0.1, respectively (Bigazzi & Figliozzi, 2015; Chowdhury & Alam, 2012; Faria, Parker, & Faria, 2005; Martin et al., 1998; Olds et al., 1995; Wilson, 2004). The bicycle mass m_b is sampled from a uniform distribution of 10%–30% of m, based on (Bigazzi & Figliozzi, 2015; Wilson, 2004); m_b (including cargo) could vary greatly for different types of bicyclists, and more research is needed to characterize m_b and A_F for utilitarian bicyclists. Note that in model D, $v^2 \geq \frac{-\mu_1}{\mu_3}$ is only a constraint beyond $v > 0$ if $G < -C_R$ (i.e., only relevant on negative grades).

For model E, 11 sets of published θ_i estimates for level walking and jogging ($G = 0$) are applied, summarized in the Supplemental Material, Table S2. Four of the θ_i sets also apply to positive grades (Glass et al., 2007; Kramer, 2010; Pimental & Pandolf, 1979), and one applies to both positive and negative grades (Kramer, 2010). Most θ_i are functions of other parameters: RMR, m, H, G, and sex. Note that in Glass et al. (2007) $\theta_2 = 0$, which leads to a linear $\dot{V}_E = f(v)$ relationship for model A_{lin}E and hence no finite MDS. We include these θ_i as a comparison case, although a linear walking energy–speed relationship is not expected to apply over about 6 km/h (1.7 m/s) (Brooks et al., 2005).

3. Results

Figure 2 gives MDS on varying road grades for illustrative 30-year-old male (81 kg) and female (69 kg) travelers by all seven models in Table 1 [with mean physiology parameters from Section 2.3 and θ_i values from Kramer (2010)]. Bicycle speeds requiring power output above the model B calibration range of 200 W are shown in a lighter shade (only relevant for A_{lin}BD). The lower end point constraint for bicycle speed is apparent in Figure 2, where the minimum bicycle MDS is $\sqrt{-\mu_1 / \mu_3}$ for all models below −2% grade (i.e., the downhill coasting speed, which increases with steeper negative grades). Energy expenditure/speed relationships ($\dot{V}O_2 = f(v)$) for these travelers are shown in Supplemental Material, Figure S1.

MDS by all models in Figure 2 is within a range of reasonable pedestrian and bicycle speeds. MDS declines with road grade for all the nonlinear models, but the influence of grade on MDS is notably larger for bicyclists than pedestrians. For grades of 0%–5%, bicycle MDS declines by 1.4–1.6 km/h (kph) per 1% grade in the log-linear models and by 0.4–0.5 km/h per 1% grade in the log models; pedestrian MDS declines by 0.07 and 0.02 km/h per 1% grade in the log-linear and log models, respectively. Energy expenditure ($\dot{V}O_2$ in lpm) increases by about $0.001vm$ with each 1% grade for both walking and bicycling, proportional to the external vertical work rate required to gain elevation: $mgvG$. Road grade has a bigger impact on bicycling than walking energy expenditure and ventilation because typical bicycle speeds are higher, and bicyclists have additional equipment mass, both leading to a higher rate of external vertical work. Further, even if the effect of grade on energy expenditure were the same in absolute terms, horizontal (non-grade-related) energy costs increase much faster with v when walking than bicycling (see Supplemental Material, Figure S1), so the influence of grade would be a smaller portion of the total energy-speed and ventilation–speed relationships for walking.

All 11 sets of θ_i were applied to the same travelers in Figure 2, 9 for level ($G = 0$) walking and 2 for level jogging (see Supplemental Material, Table S2). Median (range) walking MDS for the male is 3.4 (2.5–4.1) km/h by model A_{lin}E, 4.9 (4.2–5.5) by model A_{loglin}E, and 4.7 (3.1–6.2) by model A_{log}E. Median (range) jogging MDS for the male is 10.8 (7.7–13.2) km/h by all three models and both θ_i sets. The MDSs are mostly within the speed range of θ_i estimation data sets, which are about 3–8 km/h for walking and 8–13 km/h for jogging. As noted previously, there is no finite MDS for the Glass et al. (2007) θ_i by model A_{lin}E because $\theta_2 = 0$. MDS for the male and female are similar, as can be seen in Figure 2. The standard deviation in walking MDS among model forms for each θ_i set (0.7–1.5 km/h) is slightly higher than the standard deviation in walking MDS among θ_i for each model form (0.5–0.9 km/h); in other words, the form of $\dot{V}_E = f(\dot{V}O_2)$ has a slightly bigger impact on MDS than the selection of θ_i for $\dot{V}O_2 = f(v)$. As noted previously, A_{lin} is not expected to apply over a wide range of energy expenditures; it is included in this analysis for comprehensiveness but excluded from the remaining figures.

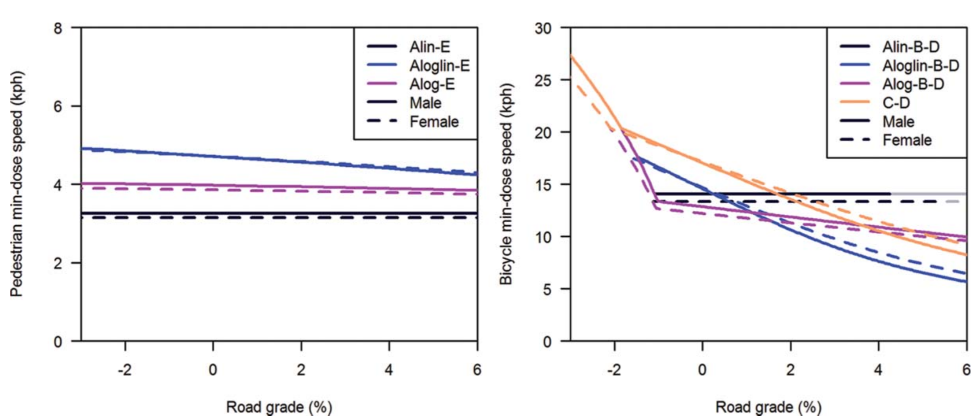

Figure 2. Pedestrian (left) and bicycle (right) MDS on varying road grades for illustrative male (solid lines, age 30, 81 kg) and female (dashed lines, age 30, 69 kg) travelers.

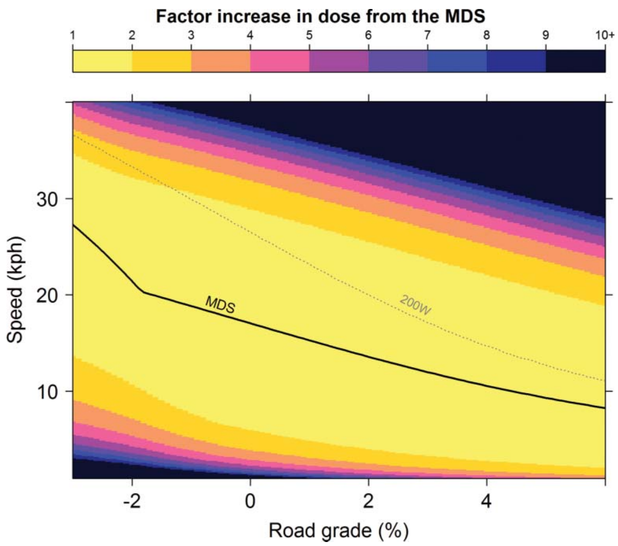

Figure 3. Factor increases in inhalation dose at bicycle speeds above and below the MDS (male traveler, age 30, 81 kg).

The impact of deviating from the MDS on $\dot{I}_d$ while bicycling is illustrated in Figure 3: the MDS for the same 30-year-old, 81-kg male traveler by model CD is the black line, and the shaded areas above and below represent factor increases in $\dot{I}_d$ from the MDS at varying road grades. $\dot{I}_d$ doubles over a relatively wide speed range of about ± 10 km/h from the MDS. Outside of this range, $\dot{I}_d$ increases more rapidly: $\dot{I}_d$ grows from double to triple the value at the MDS with a speed change of less than 3 km/h. Figure 3 shows that small deviations from the MDS have relatively little effect on $\dot{I}_d$, but large deviations can lead to dramatically higher inhalation doses. Even at the MDS, $\dot{I}_d$ increases quickly with road grade; $\dot{I}_d$ at the MDS is 32%, 68%, and 200% higher at 1%, 2%, and 5% grades, respectively, than at 0% grade (Figure S2 in the Supplemental Material gives the inhalation volume in liters per km on the same speed-grade plane as Figure 3). Note that the high-speed and high-grade ventilation estimates are above the parameter calibration range of 200 W (included in Figures 3 and S2).

Figure 4 gives median and interquartile range (IQR) bicycle MDS for the synthetic population (see Section 2.3), including the same 200 W reference line from Figure 3. The MDS IQR width is about 2–5 km/h over a wide range of grades. The widest IQR is for the log-linear models (A_{loglin}BD and CD), for which the main influencing factors on MDS are C_D, β_{loglin}, and γ_1 (the MDS at zero-grade changes by 1–3 km/h over the IQR of these factors). The main influencing factors for the other two models (A_{lin}BD and A_{log}BD) are m, C_D, and δ_0 (the MDS at zero-grade changes by about 1 km/h over the IQR of these factors). Age, RMR, and C_r are comparatively minor factors: MDS changes by less than 0.5 km/h over the IQR of these factors. For all three pedestrian models using θ_i from Kramer (2010), the MDS IQR width is 1–2 km/h, stable across grades and most sensitive to m, RMR, δ_0, and β_{loglin}.

Metabolic Equivalent of Task (MET) is a standardized measure of energy expenditure, normalized to RMR; light-, moderate-, and high-intensity physical activity have been delineated by thresholds of 1.5, 3, and 6 MET, respectively (U.S. Environmental Protection Agency, 2009). Figure 5 gives median and IQR of MET at bicycle MDS for the synthetic population, with MET $= \dfrac{\dot{V}O_2}{\text{RMR}}$ and $\dot{V}O_2$ calculated from model BD. At zero grade, MET at MDS for most of the population by all models is within the moderate-intensity physical activity range (3–6 MET). As MDS falls with road grade (Figure 4), MET at the MDS still increases; MET at the MDS is in the high-intensity physical activity range (MET > 6) for most of the population on positive grades over 2% or 3%. The median population value for MET at MDS by all models is within a range of less than 2 MET for road grades up to 2%.

For zero-grade walking, MET at the MDS is also mostly within the moderate-intensity physical activity range by all three models; median (IQR) MET at MDS for the synthetic population by models A_{lin}E, A_{loglin}E, and A_{log}E is 3.6 (2.3–5.0), 4.4 (2.8–5.7), and 4.4 (2.9–6.1), respectively, using θ_i from Kramer (2010). MET at MDS is less affected by grade for walking than for bicycling (as discussed in Figure 2); at 5% positive grade median (IQR) MET at MDS is still mostly in the moderate-intensity physical activity range: 4.2 (2.7–5.7), 4.8 (3.1–6.1), and 5.0 (3.3–7.0) by models A_{lin}E, A_{loglin}E, and A_{log}E, respectively. Across a grade range of -2% to 8%, the median population value for MET at walking MDS by all three models is within a range of less than 1 MET. The width of the population IQR for MET at walking MDS is about 3 MET (consistent across grades), which is slightly wider than the population IQR for MET at bicycling MDS (Figure 5).

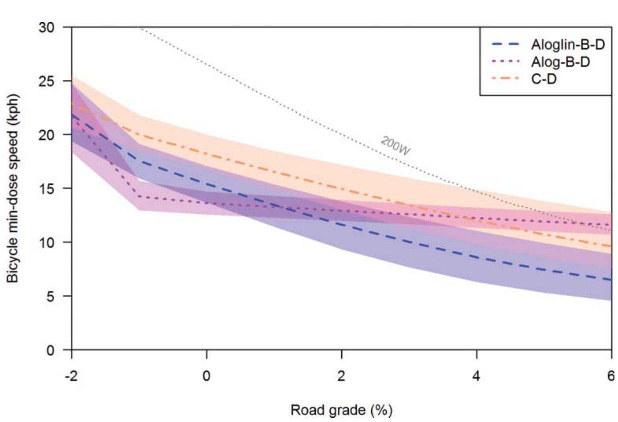

Figure 4. Median (lines) and IQR (shading) of bicycle MDS for synthetic population.

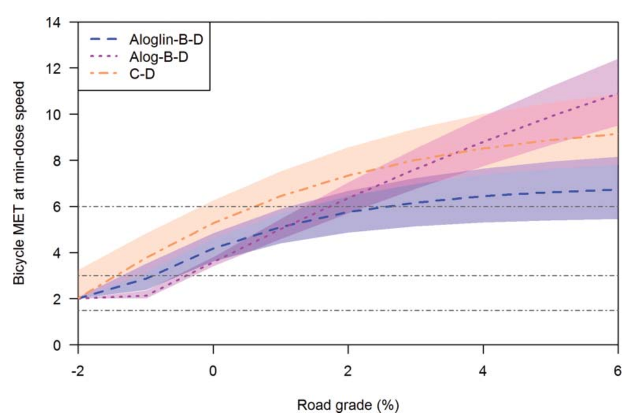

Figure 5. Median (lines) and IQR (shading) of MET at bicycle MDS for synthetic population, with physical activity thresholds at 1.5, 3 and 6 MET.

Table 2. Zero-grade MDS and MET at MDS for synthetic population by age and sex.

		Bicycle[1]		Pedestrian[2]	
Sex	Age	MDS median (IQR)	MET at MDS median (IQR)	MDS median (IQR)	MET at MDS median (IQR)
Male	<20	13.3 (11.7–14.8)	3.4 (3.3–3.6)	3.4 (2.6–4.5)	2.3 (1.3–3.6)
Male	20–60	14.5 (13.8–15.3)	3.6 (3.4–3.8)	4.5 (3.5–5.4)	4.1 (2.8–5.5)
Male	>60	14.4 (13.5–15.3)	3.9 (3.7–4.1)	4.8 (4.0–5.7)	5.1 (3.7–6.7)
Female	<20	12.5 (11.2–13.8)	3.4 (3.3–3.6)	3.5 (2.4–4.4)	3.0 (1.6–4.8)
Female	20–60	13.1 (12.4–13.9)	3.6 (3.5–3.8)	4.3 (3.2–5.4)	5.1 (3.0–7.3)
Female	>60	13.3 (12.6–14.1)	3.9 (3.7–4.1)	4.7 (3.6–5.5)	5.9 (4.1–7.8)

[1]Model A_{log}BD.
[2]Model A_{log}E using θ_i from Kramer (2010).

Table 2 gives zero-grade MDS and MET at MDS by sex and age for the synthetic population, using models A_{log}BD and A_{log}E, with θ_i from Kramer (2010). For adults aged older than 20 years, MDS is similar between the sexes and has a narrow IQR of at most 2 km/h for both modes. Bicycle MET at MDS for adults is also similar between the sexes and has a narrow IQR of at most 0.4 MET; walking MET at MDS is higher for women and has a wider IQR. MET at MDS for adults is slightly higher for walking than bicycling but similar between the modes and generally in the moderate-intensity physical activity range of 3–6 MET. Travelers aged younger than 20 years, which include children, have lower MDS and MET at MDS than those older than 20 years, primarily due to lower body mass.

4. Discussion

The MDS equations and results in the previous sections strongly support the existence of a finite MDS for pedestrians and bicyclists. Although a simple linear formulation of the $\dot{V}_E = f(v)$ relationship (model A_{lin}E with $\theta_2 = 0$) leads to an infinite walking MDS, nonlinearities are known to exist toward the upper range of walking speeds in both $\dot{V}_E = f(\dot{V}O_2)$ and $\dot{V}O_2 = f(v)$ (Brooks et al., 2005; Kramer, 2010; McArdle et al., 2010). The A_{lin} model is not expected to be representative for exercise intensities over about 6 MET. Even using a linear $\dot{V}_E = f(\dot{V}O_2)$ function, a finite bicycle MDS still exists because of the nonlinear influence of aerodynamic drag (model A_{lin}BD in Figure 2).

Zero-grade bicycling MDS for a wide range of travelers is between 12 and 20 km/h (Figure 4). Average travel speeds for urban bicyclists have been reported in the range 10–25 km/h, with the upper end being more representative of cruising speeds excluding stops (Allen, Rouphail, Hummer, & Milazzo, 1998; Bernardi & Rupi, 2015; Bigazzi & Figliozzi, 2014, 2015; Broach, Dill, & Gliebe, 2012; Int Panis et al., 2010; Jensen, Rouquier, Ovtracht, & Robardet, 2010; Menghini, Carrasco, Schüssler, & Axhausen, 2010; Nyhan, McNabola, & Misstear, 2014; Parkin & Rotheram, 2010). Thus, urban bicyclists likely ride near to or slightly faster than their MDS, with only minor increases in $\dot{I}_d$ from the minimum possible value for a given pollutant concentration (Figure 3). Zero-grade walking MDS for a wide range of travelers is between 2 and 6 km/h. Self-selected walking speeds have been reported as 4–6 km/h, again within the upper range of the MDS (Blessey, Hislop, Waters, & Antonelli, 1976; Browning, Baker, Herron, & Kram, 2006; Cunningham, Rechnitzer, Pearce, & Donner, 1982; Levine & Norenzayan, 1999; Li et al., 2012). Furthermore, speed reductions of about 0.05 and 1.4 km/h per 1% grade have been observed for walking and bicycling, respectively (Minetti, Boldrini, Brusamolin, Zamparo, & McKee, 2003; Parkin & Rotheram, 2010), remarkably close to the rates at which the MDS falls with road grade by the nonlinear models in this study. Self-selected jogging speed is about 10 km/h (Minetti et al., 2003), again near the MDS.

Adults walking or bicycling on level ground are expected to generate the MDS at a moderate-energy intensity level (3–6 MET). MDS is lower for bicyclists on grades over 2%–3% but at a high-energy intensity level (over 6 MET), pedestrian MET at MDS increases only slightly with grade. Utilitarian walking and bicycling are typically at 4–7 MET, while sport bicycling and running are at higher intensities of up to 16 MET and those walking, jogging, and bicycling for regular exercise are likely in between (Ainsworth et al., 2011; U.S. Environmental Protection Agency, 2009).

Variability in the calculated MDS in this study is due to both model forms and interpersonal parameter differences. For a particular traveler, walking MDS varies within a range of about 3 km/h with different model forms and θ_i sets; bicycle MDS varies within a range of about 5 km/h with different nonlinear model forms. For a particular model form, population IQR width is 1–2 km/h for walking and 2–5 km/h for bicycling. Other than road grade, the main interpersonal parameters correlated with MDS are body mass, slope coefficients in the ventilation–energy expenditure models (β_i), and drag coefficient for bicycles. Higher m increases MDS, while higher β_i and C_d decrease MDS, and all three factors increase inhalation dose at a given speed. As noted previously, higher β_i values are associated with children, less fit travelers, and travelers with obesity or respiratory diseases, which suggests a potential disparity in the effects of active travel speed on pollution dose and health.

More fit travelers are expected to have a lower β_i, which leads to lower $\dot{I}_d$ but higher MDS. Consistent with this effect of fitness on MDS, self-selected walking speed is positively associated with fitness (Cunningham et al., 1982). An IQR reduction in β_{loglin} (1.2–0.7) is associated with a 3 km/h higher bicycle MDS (14–17 kph); observed distributions of urban bicycle speeds across individuals (Bernardi & Rupi, 2015; Int Panis et al., 2010) suggest an IQR width of about 4 km/h. Hence, if faster bicycling is associated with fitter bicyclists, urban bicycle speeds could roughly coincide with MDS across fitness levels.

Individuals bicycling for exercise or sport likely exceed their MDS regardless of fitness level; 95th percentile MDS only reaches 19 km/h at zero grade (4 km/h above the median). Energy expenditure increases faster than inhalation dose with speeds up to about 50% over the MDS, after which dose increases more rapidly. Both energy expenditure and inhalation dose more than double with a 70% speed increase from the MDS, and increase by a factor of four with a doubled speed. In percentage terms, the inhalation dose penalty of exceeding the MDS is comparable to the exercise gains, although the trade-off in terms of health outcomes cannot be directly compared without further assessment, which is left for future work.

Urban active travelers potentially weigh many factors when choosing a speed including travel time, energy expenditure, comfort, and perceived safety; the full set of preferences leading to observed active travel speeds has not been established (Browning et al., 2006; El-Geneidy, Krizek, & Iacono, 2007). Air pollution inhalation is unlikely to be a primary motivation, and yet utilitarian pedestrians and bicyclists appear to choose approximately minimum-dose travel speeds. One possible explanation is similar effects of v on $\dot{V}O_2$ and $\dot{V}_E$ and a propensity to minimize total trip energy expenditure.

The walking MDS is supported by a similar "optimum" speed for minimum energy expenditure $\left(\dot{V}O_2\right)$ per unit distance, reported in past studies as 4–5 km/h (Browning et al., 2006; Ralston, 1958; Saibene & Minetti, 2003; van der Walt & Wyndham, 1973). The existence of a MDS partially contradicts two previous studies that concluded faster walking and bicycling leads to lower absorbed doses of air pollution (McNabola, Broderick, & Gill, 2007; Nyhan et al., 2014). The discrepancy could be due in part to speed comparisons in those studies near to the MDS (5–8 km/h walking and 8–20 km/h bicycling). In addition, McNabola et al. (2007) applied a linear $\dot{V}_E = f(v)$ function, which generates an infinite MDS as discussed in Section 2; the bicycle $\dot{V}_E = f(v)$ function was regressed on data from a single subject in a laboratory, and so the influence of aerodynamic drag (a key nonlinearity) was likely not included. Nyhan et al. (2014) calculated bicyclist $\dot{V}_E$ using a neural network model for which the main $\dot{V}_E = f(v)$ relationship was also linear (although interaction terms of v with road grade and wind were included as smoothed functions). Both studies modeled absorbed dose rather than inhaled dose, but in McNabola et al. (2007), absorbed dose was proportional to cumulative breath volume and hence inhaled dose. Nyhan et al. (2014) modeled absorbed dose of particulate matter, for which the MDS could only be lower than for inhaled dose because deposition fraction of inhaled particulate matter is equal or higher at higher $\dot{V}_E$ (Daigle et al., 2003; Löndahl et al., 2007).

The broad set of models and parameters used in this paper indicate the existence of minimum-dose active travel speeds near to observed speeds, but a number of uncertainties and limitations require further study. Physical and physiological parameters (body mass, drag coefficient, β_i values) are key uncertainties in this analysis because little information exists on their distributions for urban travelers. Individual parameter distribution estimates were used in a synthetic population analysis, but the joint distributions are unknown, and active travelers likely vary in certain characteristics from the broader population. For example, fitter individuals might be more likely to engage in active travel and have lower values of both β_i and m, with offsetting impacts on MDS.

Another source of uncertainty is the pedestrian energy expenditure parameters (θ_i), which few studies have quantified at varying grade (see Supplemental Material, Table S2). Power requirements for bicycling at varying speed and grade are more readily computed, but $\dot{V}O_2$ and $\dot{V}_E$ at high power output need further investigation. This analysis assumed that human mechanical efficiency (reflected in δ_1) was independent of power output. If efficiency were to decrease with power, δ_1 would increase and the MDS would decrease (and vice versa)—but the relationship between power and efficiency is not well established and may be influenced by equipment, cadence, training, and other factors (Faria et al., 2005; Hopker, Coleman, & Wiles, 2007; Moseley, Achten, Martin, & Jeukendrup, 2004; Moseley & Jeukendrup, 2001). The bicycle $\dot{V}O_2$ formulation also neglects the potential for insufficient bicycle gearing to limit extreme power/speed combinations at moderate cadences.

This study was limited to steady-state MDS, which excludes stop/start events during a trip; speed dynamics will be addressed in future work. The optimal target cruising speed when accelerating from a stop would likely be lower than the steady-state MDS due to the additional energy input required. Ground-level wind was also excluded from this analysis; the MDS would be lower for someone traveling in a headwind and higher for someone in a tailwind. The wind effect would apply to both pedestrians and bicyclists, although no known model of walking $\dot{V}O_2$ explicitly includes wind. The effect of active travel speed on absorbed dose will also be examined in future work. As noted previously for particulate matter, due to increasing deposition fraction with exercise, MDS is potentially lower for absorbed dose of particulates than inhaled dose. On the other hand, blood concentrations of volatile organic compounds can reach equilibrium with exposure air over the course of a trip, which would have the opposite effect of reducing absorbed fraction of inhaled mass with exercise (Astrand, 1985; Bigazzi, Figliozzi, Luo, & Pankow, 2016), and potentially lead to a higher MDS for absorbed dose than inhaled dose. For other pollutants such as carbon monoxide, absorbed fraction of inhaled mass is unlikely to be influenced by exertion level, and so, MDS would be similar for absorbed and inhaled doses.

Lastly, this paper examines the impact of speed on active traveler pollution dose, but many other factors also influence pollution dose and related health impacts. For example, pollutant concentrations, C in Equation (1), vary substantially throughout an urban road network and are affected by meteorology, road infrastructure, near-road land use, and many other factors. A broad range of strategies can be used to reduce air pollution risks for active travelers, including development of urban transport networks with more separated bicycle and pedestrian infrastructure, pollution-specific routing recommendations for active travelers, and a general reduction in emissions through vehicle, fuel, and travel controls (Bigazzi & Figliozzi, 2014; Kaur, Nieuwenhuijsen, & Colvile, 2007).

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