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Respiratory ventilation and inhaled air pollution dose while riding with a conventional and an electric-assisted cycle along routes with different elevation profiles

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ABSTRACT

Background: Differences in physical effort between cycling for transportation on an electric-assisted cycle (EAC) and a conventional cycle (CC) were previously studied. The effect of cycle type on respiratory ventilation and inhaled air pollution dose remains unclear.
Objective: The first aim was to predict respiratory ventilation while cycling on a conventional and electric-assisted cycle taking into account personal and route characteristics. The second aim was to predict the dose of inhaled pollutants while cycling on a conventional and electric-assisted cycle using the same independent variables.
Methods: Nineteen participants performed a maximal exercise test (lab test) and four cycling trips (field test): flat with CC and EAC, and hilly with CC and EAC. During each trip, heart rate, respiratory ventilation, oxygen uptake, and carbon dioxide production were measured continuously with a portable metabolic system. Cycling time, speed and distance as well as GPS coordinates were also recorded continuously. The ATMO-Street air pollution model was used to estimate black carbon (BC), nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$ and PM_{10}) inhaled doses post hoc. Factors impacting respiratory ventilation and the dose of inhaled pollutants were estimated through linear mixed modelling including laboratory and field measurements.
Results: Mean respiratory ventilation was predicted based on sex (-7.78 L/min for women), cycle type (-17.61 L/min for EAC), height gain (+0.07 L/min) and speed (+1.30 L/min). Inhaled dose of pollutants both for BC dose/km and BC dose/min was primarily predicted by cycle type (-31.62% and -34.68% for EAC compared to CC, respectively). Results were similar for the other pollutants.
Conclusions: Cycle type, sex, speed and route topography contribute to the respiratory ventilation and the use of an EAC reduces the dose of inhaled pollutants by 33% compared to the CC. Future

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projects could develop an app that predicts the cleanest route in real-time based on physical effort and ambient air pollution to increase the health benefits of cycling.

1. Introduction

To date, physical inactivity continues to be a major societal concern (WHO, 2018). Cycling, either for recreational purposes or for transportation, can contribute to achieve the target of physical activity entailing weekly exercise of 150 min of moderate intensity (Stenner et al., 2020; Bull et al., 2020). It has already been demonstrated that cycling on a conventional cycle (CC) improves physical fitness, reduces cardiovascular risk factors, lowers the risk of developing cancer and decreases all-cause mortality(Celis-Morales et al., 2017; Oja et al., 2011; Gordon-Larsen et al., 2009). Despite its advantages, CC is often shunned due to the route topography, distance to be covered, limited time availability for transport and inconveniences such as arriving sweating or out of breath at destination (de Geus et al., 2019; Van Cauwenberg et al., 2018). In contrast to the use of the CC, the electric-assisted cycle (EAC) is increasingly used as a means of transportation(Fishman and Cherry, 2016). Factors contributing to its popularity include reduced physical effort, especially on hilly routes, and reduced perspiration compared to CC, getting physical activity, the ability to continue cycling despite a physical limitation, and environmental benefits(Bourne et al., 2018, 2020)." Barriers to the use of EAC include safety concerns, battery concerns, social stigmas, exerting less physical activity and effort as compared to CC(Bourne et al., 2020).

However, in terms of physical activity, using an EAC results in less exposure time and a lower intensity of physical effort compared to a CC(Berntsen et al., 2017; Gojanovic et al., 2011). On hilly and flat routes, oxygen uptake, heart rate and power output, all indicative for physical effort, are lower when cycling with an EAC compared to a CC (Bourne et al., 2018; Berntsen et al., 2017). Moreover, it has been demonstrated that the more motorized assistance is provided, the lower the cycling intensity will be(Bourne et al., 2018). However, due to the higher speed, the lower intensity and the lower perceived exertion of EAC, more and longer journeys are carried out by EAC compared to CC, resulting in a higher total energy expenditure and physical activity(Stenner et al., 2020; Castro et al., 2019).

Another way of looking at physical effort and measuring the impact of cycling on health is by means of respiratory ventilation. The ventilation rate is positively correlated with the intensity of the effort and an exponential relationship between both is demonstrated (Zuurbier et al., 2009; Gastinger et al., 2008). At a certain point during an effort, depending on variables such as intensity and physical fitness level, ventilation will increase non-linearly. This is called the ventilatory threshold (VT) and reflects the onset of lactic acidosis and an increment in the contribution of the anaerobic system(Ghosh, 2004). Cycling above the ventilatory threshold contributes to a higher perceived effort and results in a disproportional increase in ventilation per cycling speed(de Geus et al., 2007). Future investigations are needed to evaluate the influence of cycle type (CC vs EAB) in combination with route topography on the respiratory ventilation and to determine whether people cycle at or above the ventilatory threshold itself.

In addition to the physical activity benefits of cycling, a detrimental factor often neglected when considering the net health benefits must be taken into account, namely exposure to traffic-related air pollution(Int Panis, 2010). Traffic-related air pollution contains several pollutants, including amongst others, black carbon (BC), particulate matter (PM) with an aerodynamic diameter smaller than 10 μm (PM_{10}) or smaller than 2.5 μm ($PM_{2.5}$) and nitrogen dioxide (NO_2).

The uptake of BC, PM and NO_2 via respiratory ventilation is associated with adverse short- and long-term health effects(Laeremans et al., 2018; Cepeda et al., 2017; Celis-Morales et al., 2017; Bigazzi and Figliozzi, 2014; Gordon-Larsen et al., 2009; Pope et al., 2002). Changes in vascular tone, increased oxidative stress, decreased brain-derived neurotrophic factor, pulmonary inflammation and stimulation of pulmonary irritant receptors have been demonstrated as short-term effects(Bos et al., 2011; Jacobs et al., 2010; Peretz et al., 2008, Mills et al., 2005; Zanobetti et al., 2004). Acute negative changes in lung function and heart rate variability have also been identified(Nyhan et al., 2014; Strak et al., 2010). In addition, a significant increase in throat and chest pain has been noted(Giles et al., 2018). More recent evidence nuanced the negative health effects as no changes in lung function, in blood biomarkers or in systemic inflammation and oxidative stress were found immediately after cycling(Cole et al., 2018).

An increased respiratory ventilation while cycling is associated with an increased amount of inhaled pollutants and pulmonary deposition(Daigle et al., 2003; Dons et al., 2017). An average minute ventilation rate 4.3 times higher in conventional cyclists compared to car drivers using the same route, and an inhaled dose of pollutants 4 to 9 times higher in cyclists as opposed to car drivers have been demonstrated(Int Panis et al., 2010). As indicated in the extensive review of Bourne and colleagues on EAB, ventilation *as such* is never reported in studies with EAB. To the best of our knowledge, no studies looked at the VT while cycling on a CC or EAB. The independent effect of cycle type (CC vs EAC) and route topography (flat vs hilly) on inhaled pollution, based on respiratory ventilation remains to be studied. This is especially important when taking into account the VT because if cycling on an EAB results in a ventilation at or under the ventilatory threshold, the inhaled dose of pollutants will be lower for the same speed as compared to cycling on a CC.

As shown in the Review of Mueller and colleagues, the health benefits of cycling on a CC (e.g. increased physical fitness, a lowered risk of developing cardiovascular diseases, etc.), still outweigh the risks of developing morbidities associated with respiratory inhalation of pollutants(Mueller et al., 2015). By identifying factors (e.g. age, gender, ventilation, …) that influence ventilation on different cycle types and by this means the inhaled dose of air pollutants, new or existing route planners could provide real-time and customised information for individuals to reduce their inhaled dose of pollution and this could create opportunities for cyclists to choose the healthiest routes.

Therefore, the aim of this study was two-fold. The first aim was to predict respiratory ventilation while cycling on a conventional and electric-assisted cycle taking into account personal and route characteristics. The second aim was to predict the dose of inhaled pollutants while cycling on a conventional and electric-assisted cycle using the same independent variables.

2. Methods

2.1. Participants

Twenty participants were recruited through social media channels and snowball sampling. Participants were included if they were between 18 and 50 years old, available during typical office working hours, living in the Brussels area and having previous experience with riding an (electric-assisted) cycle for transportation purposes. They were excluded if they were currently smoking or if they had a cardiovascular or respiratory disorder. Participants were informed about the study protocol and all provided their written consent. Furthermore, all participants underwent a medical screening conducted by a sport physician to ensure safe participation(ACSM, 2005). One participant did not receive approval for further participation in the field tests, resulting in nineteen included participants (Table 1).

The study was approved by the Medical Ethics Committee of the university hospital of the Vrije Universiteit Brussel (B.U.N. 143201941464).

2.1.1. Medical screening and laboratory testing

Laboratory testing was conducted to determine the physical fitness ($VO_{2\text{-}max}$) and ventilatory threshold of the participants and to determine the intensity (based on HR_{max}, $VO_{2\text{-}max}$) at which the participants cycled during the field test. As mentioned above, laboratory testing started with a medical examination by a sports physician, including a spirometry test and electrocardiogram at rest. Spirometry was used to measure forced expiratory volume in the first second (FEV1), peak expiratory flow (PEF) and forced vital capacity (FVC). In three participants spirometry was not carried out due to a technical breakdown of the spirometry device. Participants who received sports medical approval (based on i.e. electrocardiogram at rest), were invited to perform a graded exercise test (GXT) on an electrically braked cycle ergometer (Ergoselect 100, Ergoline, Bitz, Germany). They started with a warm-up of 5 min at 50 Watts and were asked to maintain a cadence of 70–90 rotations per minute (RPM). Immediately thereafter, the actual test started at 50 Watts and every 6 s, the resistance increased by 1 Watt. The GXT was terminated once volitional exhaustion was reached or when a cadence of at least 70 RPM could no longer be maintained. During the GXT, heart rate (HR) was continuously measured by an electrocardiogram. The participants wore a flexible well-fitted mask covering mouth and nose. Oxygen uptake (VO_2), carbon dioxide production (VCO_2), tidal volume, and breathing frequency, were measured by means of a portable ergospirometer, in breath-by-breath modus (K5®, Cosmed, Italy) attached to the participant's back (typical error < 2%)(Winkert et al., 2020). The K5® was calibrated according to the manufacturer's guidelines before each GXT test.

Respiratory ventilation (VE; tidal volume x breathing frequency), metabolic equivalent (MET) and respiratory exchange ratio (RER) were computed during GXT and recovery phase by the OMNIA software (Cosmed, Italy). RER was defined as the ratio between volume of exhaled carbon dioxide and consumed oxygen. The MET was calculated based on VO_2 and measured body weight (1 MET = 3.5 mL/kg.min). Ventilatory threshold (VT) was determined by the V-slope method for every GXT(Hansen et al., 2007). VT was defined as the point where respiratory ventilation raised disproportionately to the increase in oxygen consumption. VT of three participants could not be calculated due to the complexity of the curve. $VO_{2\text{-}max}$ and VE_{max} were defined as the highest values attained during the GXT over 30 s. Maximum heart rate was defined as the highest heart rate measured during the test. Medical screening and laboratory testing were performed in November 2019.

2.2. Field testing

After completion of the laboratory testing, at least one day of rest was provided to recover. All field tests were performed in November and December 2019 and took place during daylight, under dry weather conditions and mostly on separated cycle infrastructure to ensure safety of the participants. The trips were performed in Brussels – a densely populated city in Belgium – in normal traffic conditions and in respect of traffic rules including stops at traffic lights.

Each participant performed four tests in four different conditions: flat terrain with a conventional cycle (CC), flat terrain with an electric-assisted cycle (EAC), hilly terrain with a CC, and hilly terrain with an EAC. Every predefined route had to be cycled various times according to the length of the route so that all trips lasted approximately 30 min.

Table 1
Participants' characteristics.

	Men (N=10)	Women (N=9)
	Mean ± SD	Mean ± SD
Age (yr)	35.8 ± 12.5	33.0 ± 10.9
Length (cm)	179.7 ± 5.4	169.2 ± 5.4
Weight (kg)	75.4 ± 10.1	67.1 ± 7.5
BMI (kg/m^2)	23.32 ± 2.78	23.43 ± 2.31
Body fat (%)	18.56 ± 6.28	32.20 ± 4.41

BMI= body mass index, SD= standard deviation.

Five possible routes, with the same start and end point, of which two were flat and three were hilly, were mapped out (Fig. 1, A). The distinction between flat and hilly was made based on altimeters. The order of cycle type and route to be cycled was randomized. If the participant executed more than one condition on the same day, at least 2 h of recovery time was provided to ensure full recovery. Full recovery was objectified based on the return to resting heart rate.

With the CC, men rode a men's cycle (Oxford, Highland, Tracking X-perience) and women a women's cycle (Thomson 'Cosmos'). The EAC used was unisex (Gazelle, Innergy Orange) and could produce up to 250 Watts at a maximal speed of 25 km/h. Several support modes were available, but maximal support was imposed for all trials. Before departure, the saddle was adjusted to suit the participant's comfort.

The participants followed a predetermined route shown on a smartphone affixed to the steering wheel. The participants were instructed to cycle at their self-chosen pace and gear settings. Every participant was accompanied by an observer of the research team who could intervene in case of (mechanical or routing) problems. The observer always stayed at the same distance behind the participants in order to not influence the cycling speed. No incentives or verbal feedback were provided during the field tests.

During each test, HR was continuously measured by means of a Garmin chest strap and sent to the K5® (Cosmed, Italy). VO_2 and VCO_2 were measured on a breath-by-breath basis with the same device as used during the GXT (K5®, Cosmed, Italy), which was attached to the participant's back. Before each ride, the K5® was calibrated according to the manufacturer's guidelines. Cycling time (sec), speed (km/h) and distance (m) as well as GPS coordinates were continuously recorded by the K5®. The K5® was used to determine the number of stops (speed drops to 0 km/h, for example at traffic lights) during each field test. Respiratory ventilation (VE), respiratory exchange ratio (RER) and Metabolic Equivalent (MET) were computed by the OMNIA K5® software.

When the intensity exceeds the ventilatory threshold (VT) a disproportional increase in ventilation compared to oxygen uptake or cycling speed occurs. This would negatively influence the exposure to air pollution as ventilation and exposure time increases. Therefore, the % of cycling time above the VT, that was determined during GXT, was calculated (%TimeVT). Cycling intensity was determined based on the comparison of the oxygen consumption and heart rate during GXT and the field trips (%$VO_{2\text{-max}}$ and %HR, respectively) and METs.

2.3. Data processing

Breath-by-breath methods of indirect calorimetry can produce 12 data points/min at rest to more than 60 data points/min during exercise at maximal exercise intensity. To remove the temporal asymmetry in the data, a custom written script was created in Matlab (2019). Artefacts in the breath-by-breath data were removed using a 15-breaths average artefact detection(Robergs et al., 2010).

Total height gain and slopes along the routes were derived in a GIS system from the European Digital Elevation Model version 1.1 (EU-DEM) that has a resolution of 25 m (Fig. 1, B). As a measure of steepness of a trip, the 90th percentile of a rolling mean slope of

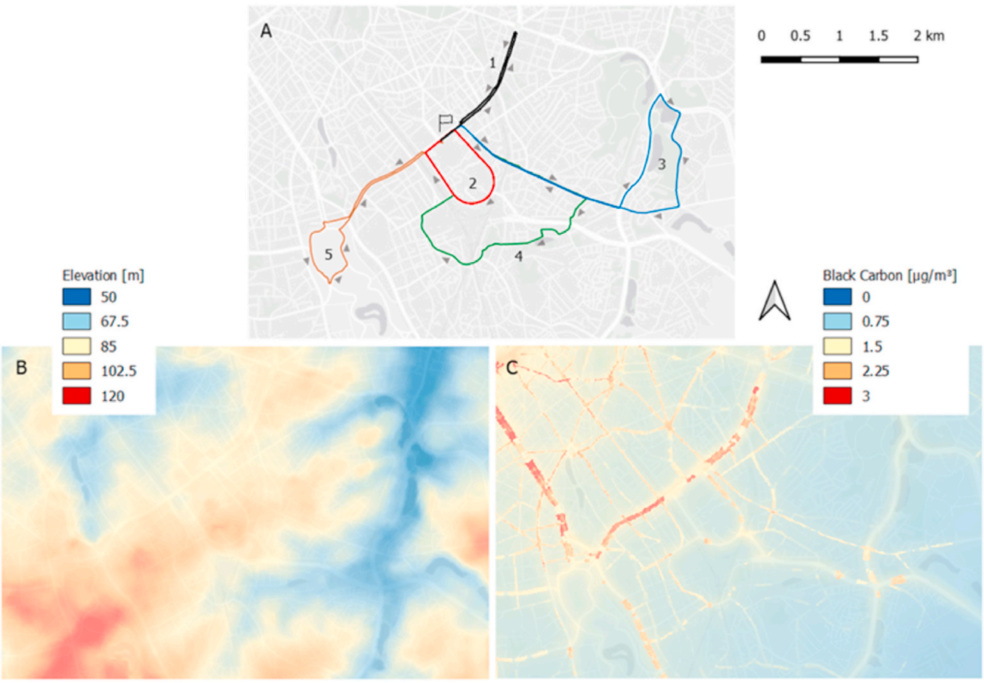

Fig. 1. The study area in Brussels with the cycling routes. Panel A shows the routes with indication of the direction (arrows) and the starting point (flag). Routes 1 and 5 were on flatter terrain; 2, 3 and 4 were hillier. The European Digital Elevation Model of the surroundings (panel B) and the black carbon concentrations from the ATMO-Street model (panel C) are shown as well.

seven consecutive observations was determined (Slope_P90).

Air pollution along the routes was derived from the ATMO-Street air pollution model (annual average concentration for the reference year 2018) for BC, $PM_{2.5}$, PM_{10} and NO_2 (Fig. 1, C).The ATMO-Street model is a combination of three existing models: the RIO interpolation model (the interpolation of air quality measurements), the bi-Gaussian dispersion model IFDM (the calculation of air quality based on meteorological data and the emission of air pollutants) and the OSPM model (the calculation of the impact of street canyon effects)(Lefebvre et al., 2013). Consequently, it incorporates regional and metropolitan background, and street canyon effects into a single air quality map with a 10-m raster-based resolution. The normalized inhaled dose for each pollutant was then calculated per km (dose/km) as well as per minute (dose/min), by multiplying the modelled air pollution by the instantaneous respiratory ventilation at each location and then dividing it by total distance (km) or total time (min) per participant per trip.

2.4. Statistical analysis

All statistical analyses were conducted in R 3.6.1(R Core Team, 2013) using the following packages: car(Fox et al., 2012), leaps (Lumley and Lumley, 2013), lme4(Bates et al., 2014) and AICcmodavg(Mazerolle and Mazerolle, 2019). Descriptive statistics were used to determine the mean, standard deviation, median, minimum and maximum for each variable. Independent sample t-tests were applied to perform data comparisons according to the cycle type. A Pearson correlation of the available trips was used to determine the relationship between all four pollutants. Subsequently, in order to examine whether the inhaled dose of pollutants per km as well as per minute differs significantly across cycle type, a Welch two sample T-test was used. The level of significance was determined at alpha = 0.05 for all analyses.

To examine the effect of the independent variables (i.e. sex, age, cycle type, distance, speed, travel time, stops, height gain, BMI, heart rate (HR), intensity of the physical effort (%HRmax and $\%VO_{2\text{-max}}$)) on the dependent variables respiratory ventilation (L/min) and inhaled dose of pollutants (dose/km and dose/min) respectively, linear mixed modelling was applied.

Multicollinearity between the different independent variables was checked by obtaining tolerance and variance inflation factor (VIF) statistics from the independent variables by running a linear regression analysis with the same dependent variable (i.e. ventilation and inhaled dose of pollutants) and all independent variables. A VIF score higher than 10.0 was interpreted as presence of multicollinearity (Field, 2009).

Subsequently, random effects were included to account for the correlation in the data due to cluster-sampling. The best random effects structure was then kept stable in the next step to compare the models with different fixed effect structures. A multi-model inference strategy was used to select a set of mixed effects regression models which best fitted the observed data(Burnham and Anderson, 2004). Besides the baseline model containing only cycle type, ten additional models were fitted, containing additive and/or interaction effects with the other independent variables (i.e. sex, age, cycle type, distance, speed, travel time, stops, height gain, BMI, HR, $\%VO_{2\text{-max}}$). The corrected Akaike Information Criterion (AICc) was used to guide model selection amongst the set of potential models. Based on the AICc, the relative weight or probability of each model (AICcWt) was computed, and the cumulative weight for the best set of models was obtained to find a confidence set that approached 90% and at last, evidence ratios (i.e. ratio of weights) were calculated. Type III ANOVA's (Satterthwaite approximations) were applied to test the significance of the main and interaction effects. Model averaging was performed for all parameters that turned up in different models in the 95% confidence set to get more accurate estimates(Burnham and Anderson, 2004). All statistical analyses were executed for both independent variables (i.e. respiratory ventilation and inhaled dose of pollutants).

Table 2
Descriptive statistics field tests (N=75 trips).

	CC (N=38)	EAC (N=37)	Men (N=10)	Women (N=9)
Distance (km)	7.28 ± 1.28	8.08 ± 2.08[a]	7.73 ± 1.73	7.62 ± 1.81
Speed (km/h)	15.9 ± 2.3	18.7 ± 3.0[a]	18.0 ± 3.0[a]	16.5 ± 2.9
Travel time (min)	26 ± 5	24 ± 4	24 ± 4	26 ± 5
Height gain (m)	87.0 ± 25.4	87.4 ± 36.7	88.6 ± 30.9	85.6 ± 32.1
Slope_P90	2.96 ± 0.99[a]	2.42 ± 0.85	2.73 ± 0.97	2.64 ± 0.95
Stops	2.5 ± 2.6	2.9 ± 3.4	2.4 ± 2.8	3.1 ± 3.2
METs	6.61 ± 1.62[a]	4.89 ± 1.41	6.22 ± 1.94[a]	5.24 ± 1.32
Ventilation (L/min)	49.49 ± 11.95[a]	35.58 ± 7.87	46.65 ± 12.40[a]	38.03 ± 10.52
Heart rate (bpm)	129 ± 18[a]	108 ± 18	113 ± 17	125 ± 23[a]
%HRmax	70.51 ± 8.69[a]	58.99 ± 7.88	61.48 ± 8.66	70.51 ± 8.69[a]
VO2 (L/min)	1.504 ± 0.375[a]	1.095 ± 0.262	1.458 ± 0.382[a]	1.125 ± 0.300
VO2 (mL/kg.min)	21.15 ± 5.02[a]	15.39 ± 3.71	19.55 ± 5.41[a]	16.90 ± 4.79
%VO2-max	48.12 ± 11.24[a]	34.77 ± 8.81	38.18 ± 9.63	45.37 ± 13.53[a]
%TimeVT	7.15 ± 12.08[a]	0.00 ± 0.00	3.40 ± 9.42	4.03 ± 9.20

Values are mean ± SD.
CC: conventional cycle; EAC: electric-assisted cycle.
%TimeVT = percentage of time the participants cycled above their ventilatory threshold (VT).
Slope_P90 = 90th percentile of a rolling mean slope of seven consecutive observations.
Significant differences reported at $p<0.05$.
[a] refers to the significant highest value(s) for the parameter with cycle type or sex.

3. Results

3.1. Descriptive statistics

Results from the laboratory test yielded a FEV_1 of 4.2 ± 0.6 L, a maximal heart rate of 182 ± 14 bpm, a VE_{max} of 108.1 ± 33.1 L/min, a VT of 79.6 ± 17.3 L/min, a RER_{max} of 1.2 ± 0.1, and a $VO_{2\text{-}max}$ of 32.3 ± 8.8 mL/kg.min. The $VO_{2\text{-}max}$ was significantly higher in men as compared to women (Mean diff = 13.1, $p<0.001$).

During the field testing, each participant cycled four routes, giving a total of 76 cycled trips. One trip had to be excluded due to a large amount of missing data, resulting in a total of 75 trips used for the data analyses. Seventy-five trips were analysed of which 38 were executed with a conventional cycle (CC) and 37 with an electric-assisted cycle (EAC). The descriptive statistics of the field tests for CC and EAC and for men and women are displayed in Table 2. The total distance and elevation travelled for the hilly routes was 111 ± 25 m and 11.8 ± 7.8 km, compared to 64 ± 15 m and 9.8 ± 7.9 km for the flat routes, respectively.

Distinguishing on the basis of sex showed that men had a significantly higher VO_2 (19.5 ± 5.4 mL/kg.min), higher respiratory ventilation (46.6 ± 12.4 L/min) and lower heart rate (113 ± 17 bpm) compared to women (16.9 ± 4.8 mL/kg.min, 38.0 ± 10.5 L/min and 125 ± 23 bpm, respectively) averaged over all cycling conditions. In addition, men cycled at a lower percentage of their HR_{max} (61.5 ± 8.7%) and $VO_{2\text{-}max}$ (38.2 ± 9.6%), and at higher METs (6.2 ± 1.9) than women (70.5 ± 8.7%, 45.4 ± 13.5% and 5.2 ± 1.3, respectively).

In terms of height gain and number of stops, no significant differences were observed between cycle types. For the CC, METs of 6.6 ± 1.6, a heart rate of 129 ± 19 bpm, and a respiratory ventilation of 49.5 ± 12.0 L/min were noted. These values were significantly higher compared to the trips done with the EAC: 4.9 ± 1.4, 108 ± 18 bpm and 35.6 ± 7.9 L/min, respectively. When comparing respiratory ventilation with the ventilatory threshold, respiratory ventilation exceeded the threshold 7.2% of the time when riding a CC, and only 0.01% of the time when riding an EAC. This illustrates that cycling with assistance is performed at a lower intensity and higher speed and thus requires less effort as compared to cycling on a CC.

3.2. Best fit models' prediction

Due to multicollinearity (between cycling distance and ventilation) cycling distance was excluded for further analysis (VIF score > 10).

The best fit for predicting ventilation was obtained for the model with main effects for sex, height gain, $VO_{2\text{-}max}$, speed, cycle type and $\%VO_{2\text{-}max}$ (Appendix Table A1). This model contained approximately half of the probability (AICcWt=0.49) amongst all models and was respectively 0.02 times better than the second-best model, meaning that the first and second model similarly contribute to the true underlying model. The first two models constituted an 86% confidence set. Both models in this set contain main effects of sex, $VO_{2\text{-}max}$, $\%VO_{2\text{-}max}$, cycle type and height gain indicating that these effects are likely to be part of the underlying data generating mechanism. Similarly, these procedures were applied for predicting respiratory ventilation using only route characteristics, sex and cycle type (excluding $VO_{2\text{-}max}$, $\%VO_{2\text{-}max}$), and for the prediction of the inhaled BC dose/km and dose/min. These results are presented in Table A.2-A.4, respectively.

No interaction effects were significant.

Table 3
Overview of parameter estimates, standard errors and 95% CI of model 1–2 and the model average for predicting ventilation.

		Model 1		Model 2		Model average	
		estimate	95% CI	estimate	95% CI	estimate	95% CI
Intercept	**β0**	2.73	[-17.58; 23.12]	−3.08	[-22.77; 16.53]	−0.15	[-20.41; 20.12]
Sex	**β1**	−6.01	[-13.35; 1.34]	−6.10	[-13.35; 1.16]	−6.05	[-12.99; 0.88]
Height gain	**β2**	0.06	[0.02; 0.10] *	0.06	[0.01; 0.10] *	0.06	[0.02; 0.10] *
$VO_{2\text{-}max}$	**β3**	0.51	[0.02; 0.96] *	0.46	[0.02; 0.91] *	0.49	[0.02; 0.96] *
Cycle type	**β4**	−6.17	[0.06; 0.95] *	−7.88	[-11.68; -4.11] *	−7.02	[-10.74; -3.30] *
$\%VO_{2\text{-}max}$	**β5**	0.59	[-9.09; -3.25] *	0.58	[0.41; 0.74] *	0.59	[0.42; 0.75] *
Stops	**β6**	−0.38	[-0.84; 0.07]	/	/	−0.38	[-0.84; 0.07]
Speed	**β7**	/	/	0.49	[-0.10; 1.07]	0.29	[-0.09; 1.06]
	Σ	4.53	[3.81; 5.52]	4.55	[3.82; 5.55]	/	/
	ϒ	4.45	[2.93; 6.77]	4.38	[2.86; 6.68]	/	/
	$adjR^2$	0.86	/	0.86	/	/	/

$Y_{ij} = \beta_0 + b_{0j} + \beta_1\, _{x1ij} + \beta_{2ij}\, _{x2ij} + \beta_{3ij}\, _{x3ij} + \beta_{4ij}\, _{x4ij} + \beta_5\, _{x5ij} + \beta_6\, _{x6ij} + \beta_7\, _{x7ij} + \varepsilon_{ij}$.
$b_{0j} \sim N(0; \upsilon^2)$: random intercepts for participant.
$\varepsilon_{ij} \sim N(0; \sigma^2)$: residual variance.
$j = 1 \ldots 4$, $i = 1 \ldots n_j$ (number of observations per participant).
x_1= 1 for woman (0 otherwise).
x_4= 1 for EAC (0 otherwise).
Sex= Man, Woman; Cycle type= CC, EAC; $\%VO_{2\text{-}max}$= percentage of maximal oxygen uptake.
*$p<0.05$.

3.3. Prediction of respiratory ventilation

Table 3 depicts the coefficients of the best two models predicting respiratory ventilation as well as the coefficients obtained by the model averaging. Type III ANOVA tests associated with each factor showed some significant effects. The recurring factors in the 86% confidence set (i.e., main effects of sex, height gain, $VO_{2\text{-max}}$ and $\%VO_{2\text{-max}}$) were significant in each model ($p<0.05$). The model average allowed us to retrieve more accurate estimates of the fixed effects included in the 2 models of the 86% confidence set. The averaged model indicated a positive significant effect of height gain, $VO_{2\text{-max}}$, $\%VO_{2\text{-max}}$ and a negative significant effect of cycle type. This means that respiratory ventilation increased with an increase of 1 m in height gain (+0.06 L/min). Additionally, respiratory ventilation also increased with an increment of 1 mL/kg.min in $VO_{2\text{-max}}$ (+0.49 L/min) and when cycling at a 1% higher percentage of the $VO_{2\text{-max}}$ (+0.59 L/min). The strongest predictor for respiratory ventilation was the cycle type, with an EAC that lowered the respiratory ventilation by 7.02 L/min, all other variables being equal.

We have re-run the model predicting respiratory ventilation only including variables that can be included in route planning software based on route characteristics (i.e., height gain, speed and number of stops) and on variables that can be easily provided by users (i.e., sex and cycle type) (Table 4). The averaged model indicated a significant negative effect of cycle type (-17.61 L/min for EAC as compared to CC) and sex (-6.78 L/min in women as compared to men), while significant positive effects were generated for height gain (+0.07 L/min) and speed (+1.30 L/min).

3.4. Prediction of inhaled dose of pollutants

Over the 75 trips, mean exposure was 1.74 ± 0.29 μg/m³ for BC, 13.4 ± 0.7 μg/m³ for $PM_{2.5}$, 20.8 ± 1.0 μg/m³ for PM_{10}, and 39.0 ± 6.4 μg/m³ for NO_2. Fig. 2 illustrates the inhaled BC dose per kilometre and per minute over cycle type. When riding the EAC, participants inhaled significantly less BC. Results were similar for $PM_{2.5}$, PM_{10} and NO_2. The dose ratio per distance unit (EAC over CC) for BC and NO_2 were 0.66 and for PM_{10} and $PM_{2.5}$ were 0.64. This implies that when using the EAC one inhaled roughly one third less pollution as compared to cycling on a CC. The dose ratio per time unit was 0.76 for BC, 0.77 for NO_2 and 0.74 for PM_{10} and $PM_{2.5}$, respectively.

Similarly, as for the prediction of respiratory ventilation, a regression model (Table 5) was developed to determine the impact of sex, cycle type, speed, height gain, $VO_{2\text{-max}}$ and number of stops, on the black carbon dose/km. The model average indicated cycle type (-0.080 μg/km), sex (-0.044 μg/km), height gain (+0.004 μg/km) and speed (-0.008 μg/km) as the significant parameters. Switching from CC to EAC, all other factors being equal, lowered the average BC dose/km by 0.080 μg/km. As for the black carbon dose/min (Table 6), the model average shows cycle type (-0.0025 μg/min), sex (-0.012 μg/min), height gain (+0.0002 μg/min) and speed (+0.002 μg/min) as significant predictors. In short, for both BC dose/km and dose/min the use of an EAC reduces the inhalation of pollutants by approximately 33%.

Due to the high correlation ($r>0.89$) between the different pollutants (BC, $PM_{2.5}$, PM_{10} and NO_2) only the results for BC are shown.

4. Discussion

The first aim was to predict respiratory ventilation while cycling on a conventional and electric-assisted cycle taking into account personal and route characteristics. The second aim was to predict the dose of inhaled pollutants while cycling on a conventional and

Table 4
Overview of parameter estimates, standard errors and 95% CI of model 1–3 and the model average for predicting ventilation (excluding the ventilation parameters $VO_{2\text{-max}}$, $\%VO_{2\text{-max}}$).

		Model 1		Model 2		Model 3		Model average	
		estimate	95% CI	estimate	95% CI	estimate	95% CI	estimate	95% CI
Intercept	**β0**	26.65	[16.25; 37.01]	31.11	[16.48; 45.58]	24.40	[13.78; 35.00]	27.38	[15.22; 39.54]
Sex	**β1**	−6.84	[-12.08; -1.64] *	−6.92	[-12.31; -1.59] *	−6.36	[-11.55; -1.18] *	−6.78	[-11.80; -1.77] *
Height gain	**β2**	0.07	[0.01; 0.12] *	0.07	[0.01; 0.12] *	/	/	0.07	[0.01; 0.12] *
Cycle type	**β3**	−17.58	[-21.00; -14.18] *	−16.82	[-20.65; -13.07] *	−18.92	[-22.28; -15.56] *	−17.61	[-21.27; -13.95] *
Speed	**β4**	1.27	[0.56; 1.99] *	1.05	[0.18; 1.93] *	1.76	[1.17; 2.37] *	1.30	[0.45; 2.14] *
Stops	**β5**	/	/	−0.31	[-1.02; 0.41]	/	/	−0.31	[-1.00; 0.38]
	σ	6.08	[5.11; 7.40]	5.99	[5.02; 7.30]	6.37	[5.35; 7.76]	/	/
	υ	4.48	[2.54; 7.11]	4.67	[2.70; 7.40]	4.35	[2.29; 7.01]	/	/
	adjR²	0.75	/	0.76	/	0.73	/	/	/

$Y_{ij} = \beta_0 + b_{0j} + \beta_{1\ x1ij} + \beta_{2ij\ x2ij} + \beta_{3ij\ x3ij} + \beta_{4ij\ x4ij} + \beta_{5\ x5ij} + \beta_{6\ x6ij} + \varepsilon_{ij}$.
$b_{0j} \sim N(0; \upsilon^2)$: random intercepts for participant.
$\varepsilon_{ij} \sim N(0; \sigma^2)$: residual variance.
$j = 1 \ldots 4$, $i = 1 \ldots n_j$ (number of observations per participant).
$x_1 = 1$ for woman (0 otherwise).
$x_4 = 1$ for EAC (0 otherwise).
Sex= Man, Woman; Cycle type= CC, EAC.
*$p<0.05$.

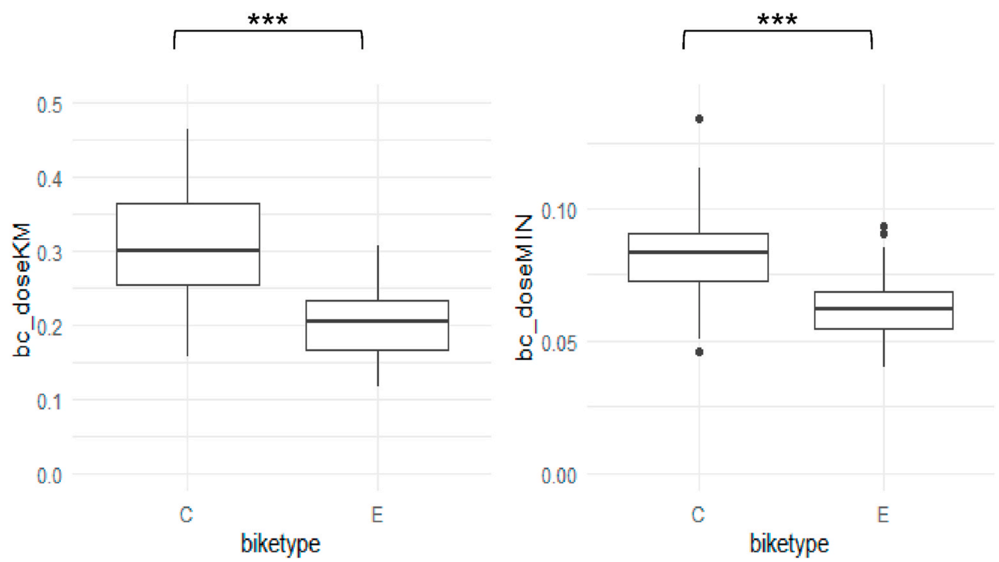

Fig. 2. Black carbon dose/km and dose/min by cycle type.
Represented are the median and the IQR (box), Q1 - 1.5* IQR and Q3 + 1.5*IQR (whiskers), and outliers (dots)Statistical significance: $p<0.001$ ***Abbreviations: bc_doseKM = inhaled dose black carbon μg per km; bc_doseMIN = inhaled dose black carbon μg per min; C: conventional cycle, E: EAC.

Table 5
Overview of parameter estimates, standard errors and 95% CI of model 1–3 and the model average for predicting bc_dose/km.

		Model 1		Model 2		Model 3		Model average	
		estimate	95% CI	estimate	95% CI	estimate	95% CI	estimate	95% CI
Intercept	**β0**	0.504	[0.432; 0.576]	0.474	[0.377; 0.572]	0.514	[0.397; 0.632]	0.498	[0.408; 0.589]
Sex	**β1**	−0.044	[-0.074; -0.014] *	−0.043	[-0.073; -0.014] *	−0.047	[-0.092; -0.002] *	−0.044	[-0.076; -0.013] *
Height gain	**β2**	−0.0004	[-0.0008; 0.0000] *	−0.0004	[-0.0008; 0.0000] *	−0.0002	[-0.0008; 0.0000] *	0.0004	[-0.0008; 0.0000] *
Cycle type	**β3**	−0.080	[-0.105; -0.056] *	−0.085	[-0.112; -0.059] *	−0.081	[-0.105; -0.056] *	−0.080	[-0.110; -0.060] *
Speed	**β4**	−0.009	[-0.014; 0.004] *	−0.007	[-0.013; -0.001] *	−0.009	[-0.014; -0.004] *	−0.008	[-0.014; -0.003] *
Stops	**β5**	/	/	0.002	[-0.003; 0.007]	/	/	0.002	[-0.003; 0.007]
$VO_{2\text{-max}}$	**β6**	/	/	/	/	−0.0003	[-0.003; 0.002]	−0.0003	[-0.003; 0.002]
	σ	0.044	[0.037; 0.053]	0.044	[0.037; 0.053]	0.044	[0.037; 0.053]	/	/
	υ	0.022	[0.000; 0.038]	0.021	[0.000; 0.037]	0.022	[0.000; 0.038]	/	/
	$adjR^2$	0.70	/	0.70	/	0.70	/	/	/

$Y_{ij} = \beta_0 + b_{0j} + \beta_1 \, _{x1ij} + \beta_{2ij} \, _{x2ij} + \beta_{3ij} \, _{x3ij} + \beta_{4ij} \, _{x4ij} + \beta_5 \, _{x5ij} + \beta_6 \, _{x6ij} + \varepsilon_{ij}$.
$b_{0j} \sim N(0; \upsilon^2)$: random intercepts for participant.
$\varepsilon_{ij} \sim N(0; \sigma^2)$: residual variance.
$j = 1 \ldots 4$, $i = 1 \ldots n_j$ (number of observations per participant).
$x_1 = 1$ for woman (0 otherwise).
$x_4 = 1$ for EAC (0 otherwise).
Sex= Man, Woman; Cycle type= CC, EAC.
*$p<0.05$.

electric-assisted cycle using the same independent variables.

Our findings indicate that cycle type, height gain, maximal oxygen uptake ($VO_{2\text{-max}}$) and percentage of maximal oxygen uptake (% $VO_{2\text{-max}}$) are significant predictors of respiratory ventilation. The multi-model inference strategy revealed that cycle type plays a substantial role in predicting respiratory ventilation as was anticipated. The second aim of this study consisted of predicting the inhaled pollutant dose. It is important to point out that the results were considered both per time unit and per kilometre. For the inhaled dose per kilometre, cycle type, sex, speed and height gain are significant predictors. This illustrates that the use of the electric-assisted cycle (EAC) significantly reduces pollutant inhalation as opposed to the use of a conventional cycle (CC) and that this reduced intake is amplified by a higher speed and by sex. The influence of being female on lowering the dose of inhaled pollution could be attributed to the differences in lung capacity between man and women(Lomauro and Aliverti, 2018).

The studies of Sperlich et al. (2012) and Berntsen et al. (2017) compared cycling intensity of CC and EAC on routes with a different

Table 6
Overview of parameter estimates, standard errors and 95% CI of model 1–3 and the model average for predicting bc_dose/min.

		Model 1		Model 2		Model 3		Model average	
		estimate	95% CI	estimate	95% CI	estimate	95% CI	estimate	95% CI
Intercept	**β0**	0.072	[0.053; 0.091]	0.068	[0.042; 0.095]	0.073	[0.041; 0.174]	0.072	[0.042; 0.095]
Sex	**β1**	−0.012	[-0.021; -0.004] *	−0.012	[-0.021; -0.004] *	−0.013	[-0.026; 0.000]	−0.012	[-0.022; -0.033] *
Height gain	**β2**	−0.0002	[-0.0003; -0.0001] *	−0.0002	[-0.0003; -0.0001] *	−0.0002	[-0.0003; -0.0000] *	0.0002	[-0.0003; -0.0001] *
Cycle type	**β3**	−0.025	[-0.031; -0.018] *	−0.025	[-0.032; -0.018] *	−0.025	[-0.031; -0.018] *	−0.025	[-0.031; -0.019] *
Speed	**β4**	0.002	[0.001; 0.003] *	0.002	[0.000; 0.004] *	0.002	[0.001; 0.003] *	0.002	[0.001; 0.003] *
Stops	**β5**	/	/	0.0002	[-0.0010; 0.0015]	/	/	0.0002	[-0.0010; 0.0015]
$VO_{2\text{-max}}$	**β6**	/	/	/	/	−0.0001	[-0.0008; 0.0007]	−0.0001	[-0.0008; 0.0007]
	σ	0.011	[0.010; 0.014]	0.011	[0.010; 0.014]	0.011	[0.010; 0.014]	/	/
	υ	0.007	[0.003; 0.011]	0.007	[0.003; 0.011]	0.007	[0.003; 0.011]	/	/
	adjR^2	0.62	/	0.62	/	0.62	/	/	/

$Y_{ij} = \beta_0 + b_{0j} + \beta_1\, _{x1ij} + \beta_{2ij}\, _{x2ij} + \beta_{3ij}\, _{x3ij} + \beta_{4ij}\, _{x4ij} + \beta_5\, _{x5ij} + \beta_6\, _{x6ij} + \varepsilon_{ij}$.
$b_{0j} \sim N(0; \upsilon^2)$: random intercepts for participant.
$\varepsilon_{ij} \sim N(0; \sigma^2)$: residual variance.
$j = 1 \ldots 4$, $i = 1 \ldots n_j$ (number of observations per participant).
x_1= 1 for woman (0 otherwise).
x_4= 1 for EAC (0 otherwise).
Sex= Man, Woman; Cycle type= CC, EAC.
*$p<0.05$.

topography with a total elevation of 102 m and 130 m for hilly routes, respectively. This was comparable to this study with a total elevation difference of 104 ± 22 m for the CC and 118 ± 26 m for the EAC along hilly routes. Furthermore, the duration of the trip was similar to Berntsen's study(Berntsen et al., 2017). The trip duration in this study amounted 24 ± 4 min for the EAC and 26 ± 5 min for CC, representing a common single trip duration for commuting purposes(Castro et al., 2019).

The percentage of maximal oxygen uptake (%$VO_{2\text{-max}}$), the percentage of maximal heart rate (%HRmax) and the metabolic equivalent (METs) are means of expressing the intensity of physical effort. In this study an average %$VO_{2\text{-max}}$ of 48% and 35% was found for CC and EAC, respectively. These values are below expectations as the literature shows rates of 57-79% and 51-55% $VO_{2\text{-max}}$ for CC and EAC, respectively(Berntsen et al., 2017; Gojanovic et al., 2011, de Geus et al., 2007). Even though these values are lower, the percent difference between CC and EAC is comparable to results in previous published research(Berntsen et al., 2017; Gojanovic et al., 2011, de Geus et al., 2007). A possible explanation for the relatively low values in this study, compared to the abovementioned studies is the study area and the rest time between trips. The de Geus et al. study – only using CC – took place in a rural environment with only flat routes where participants could cycle long distances without stops which made it possible to cycle at a higher intensity (de Geus et al., 2007). In the Berntsen study participants did not have to stop for traffic lights which could result in a higher average speed and therefore intensity(Berntsen et al., 2017). A final explanation for the discrepancy in relative intensity between the studies is that in this study participants had to wait at least 2 h between two consecutive trips and never did more than two trips per day whereas in the Gojanovic and Berntsen study participants performed 2 trips per day with only 30 min break and four trips a day with only 2 min break, respectively(Berntsen et al., 2017; Gojanovic et al., 2011). This could have resulted in an accumulation of fatigue and as a result higher respiratory ventilation values.

The percentage of the maximum heart rate (%HRmax) achieved by cycling is consistent with previously published studies(Simons et al., 2009, de Geus et al., 2007). This study found a value of 71% and 59% HRmax for the CC and EAC, respectively. This demonstrates that cycling on a CC requires a greater effort. A similar inference can be drawn from the METs. For the CC an average METs of 6.6 was calculated. This is described as vigorous physical activity and is consistent with previously reported values(Mendes et al., 2018; Berntsen et al., 2017; Sperlich et al., 2011; Simons et al., 2009). The METs of EAC was significantly lower as compared to the CC (4.9 ± 1.4 and 6.6 ± 1.6, respectively). Hence, when using the assisted cycle one can achieve a sufficiently high intensity to attain the required moderate physical activity (3–6 METs) for health benefits(Bull et al., 2020; Siman-Tov et al., 2012). Participants riding an EAC cycled faster (18.7 ± 3.0 km/h) as compared to riding on a CC (15.9 ± 2.3 km/h). This was to be expected as it has been previously shown that people ride faster and at a lower intensity on an EAC(Berntsen et al., 2017; Gojanovic et al., 2011).

Regarding the first research question of this study, this is the first study that used linear mixed modelling to predict respiratory ventilation based on personal and route variables (i.e. sex, age, cycle type, distance, speed, travel time, stops, height gain, body mass index, heart rate, intensity of the physical effort (%$VO_{2\text{-max}}$)). This study showed that mainly cycle type, cycling intensity (%$VO_{2\text{-max}}$), $VO_{2\text{-max}}$ and height gain contribute to the respiratory ventilation. The intensity of the cycling effort and the cycle type influence the respiratory ventilation: riding at higher intensity (e.g., at a higher %$VO_{2\text{-max}}$) and opting for a CC translates into delivering a greater physical effort and therefore leads to a higher respiratory ventilation. Furthermore, the results imply that when cycling on a hilly course, one will deliver a more physically demanding task and thus have a higher respiratory ventilation. This result also indicates that cycling downhill does not compensate for efforts delivered while cycling uphill.

Regarding the second research question of this study, we predicted the inhaled dose of pollutants based on sex, cycle type, speed, height gain, $VO_{2\text{-max}}$ and number of stops. Cycle type, height gain, speed and sex were significant predictors for both the inhaled dose of pollutants per km and per min. We showed that by changing from a CC to an EAC, one can reduce its inhaled dose by one third while keeping the health benefit of physical activity. When comparing exposure to pollutants relative to other means of transport, it is striking that cyclists are less exposed to pollutants but will in fact inhale more pollution because of their increased respiratory ventilation compared to car and bus commuters(Cepeda et al., 2017, de Nazelle et al., 2017; Int Panis et al., 2010). Our results show a mean black carbon (BC) dose of 0.082 ± 0.018 μg/min when using the CC and 0.062 ± 0.014 μg/min when using the EAC. For particulate matter (PM) with an aerodynamic diameter smaller 2.5 μm ($PM_{2.5}$), these were 0.65 ± 0.14 μg/min and 0.48 ± 0.10 μg/min, respectively. The BC dose per km amounted to 0.304 ± 0.069 μg/km when using the CC and 0.200 ± 0.050 μg/km when using the EAC. For $PM_{2.5}$ these values were 2.40 ± 0.43 μg/km and 1.53 ± 0.27 μg/km, respectively. In terms of the inhaled dose per km for $PM_{2.5}$ on a CC, our values are comparable to the study of Int Panis (2010) who reported a $PM_{2.5}$ dose per km of 3.4 ± 1.3 μg/km(Int Panis et al., 2010). To our knowledge, no study reported the inhaled dose of pollutants on an EAC and/or compared both cycle types within the same study population(Cepeda et al., 2017).

Although the total number of trips in this study were rather limited, our results imply that a promising solution to decrease the exposure to air pollution could be to include these kinds of data into new or existing route planners allowing real-time information on the healthiest route to be travelled by the mode of transport chosen. Route planners could include a 'cleanest' route option accounting for inhaled dose along the way. To test this possibility, the analysis for predicting respiratory ventilation was additionally ran using only variables that can easily be included in route planning software like route characteristics and motorised traffic flows (already available in route planner software) and variables that can be provided by users (i.e., sex, cycle type, speed, number of stops and height gain). This means that, in addition to reducing polluting traffic, opportunities abound to enhance cyclists' health or at least limit the negative consequences.

We opted to use the European Digital Elevation Model (EU-DEM) for the altimeters instead of the altimeters obtained by the GPS of the K5®. This decision was made due to spurious GPS jumps and because of the robustness of using the model. Nevertheless, a strong correlation ($r = 0.87$) was found between GPS elevation and EU-DEM. A possible drawback of using this model is that bridges, for example, are not taken into account. However, since the routes were without bridges, this did not affect our results. Furthermore, we also opted in favour of applying the annual average ATMO-street model to predict the inhaled dose of pollution and not perform mobile air pollution measurements. This has both advantages and disadvantages. Mobile air pollution measurements are complex, expensive, and can be subject to systematic error. The air pollution model predicts annual average concentrations; consequently, it is not subject to accidental pollution peaks or meteorological and seasonal variation making it more representative for long term exposure. On the other hand, our model was for the year 2018, while our field testing took place at the end of 2019. A low-emission zone was implemented in Brussels at the beginning of 2019. The possible positive effect of this policy on circulating pollution cannot yet be investigated. However, it is likely that the actual inhaled dose was lower than what our results show.

Both long-term and short-term exposure to traffic-related air pollution are associated with negative health effects such as cardiopulmonary mortality and morbidity(Laeremans et al., 2018; Celis-Morales et al., 2017; Gordon-Larsen et al., 2009; Pope et al., 2002). Nevertheless, the health benefits of physical activity while cycling still outweigh the risks of air pollution and crashes(Mueller et al., 2015). However, it is important to limit the risks as much as possible to enjoy the full beneficial effect. Possible solutions might include the reduction of polluting traffic and/or the construction of separate cycle infrastructure. This latter allows cyclists to move further away from the polluting traffic(Macnaughton et al., 2014; Hatzopoulou et al., 2013).

Several considerations must be taken into account in this study. Not all participants cycled the five routes with the same cycle: both were randomized. However, this means that air pollution could be higher on routes travelled by EAC for one participant, while for another air pollution was low on the routes travelled by EAC. Similarly, some of the routes required more stops because of traffic lights. This complicated a direct comparison of cycle types on one specific route. In our study, air pollution concentrations (without taking respiratory ventilation into account) were higher on the flat routes compared to the hilly routes (Fig. 1 C). This was a result of the higher traffic intensity with more stop-and-go's on the flat routes. Emissions from motorized traffic are higher uphill, so one would expect higher concentrations of traffic-related air pollution on hillier roads. Combined with higher respiratory ventilation rates uphill, this would have a multiplicative effect on inhaled air pollution dose. However due to the specific situation in our study, we could not observe this effect. In addition, it must be stressed that Brussels is a hilly city but not a mountainous area and height differences are limited compared to other cities in other parts of the world.

5. Conclusions

The electric and conventional cycles are both capable of contributing to reaching the target of moderate-intensity physical activity for health benefits. However, the electric-assisted cycle lowers the respiratory ventilation, reduces the amount of effort required to cycle and increases the cycling speed due to the electric-assistance provided. Mean respiratory ventilation was predicted based on sex, cycle type, height gain and speed, with cycle type being the strongest predictor for respiratory ventilation. Regarding ambient traffic-related air pollution, the electric-assisted cycle reduces the dose of pollution inhaled by about one third compared to the conventional cycle. These advantages permit the cyclist to choose a cycle that minimizes the inhaled dose of air pollution while performing a physical activity that helps in attaining the guidelines for physical activity.

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Declaration of competing interest

The authors declare no conflict of interest.

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Appendix

Table A.1
Overview of the best fit models predicting ventilation with different fixed effects

	Model formula (in lme4 syntax)	K	AICc	ΔAICc	AICcWt	AICcWt CumWt	ev. Ratio
1	Y ~ Sex + HG + VO_2 + TC + %VO_2 + St	9	490.14	0.00	0.49	0.49	1.00
2	Y ~ Sex + HG + VO_2 + TC + %VO_2 + S	9	490.17	0.03	0.48	0.97	1.02
3	Y ~ Sex + TC + %VO_2 + S	7	495.67	5.53	0.03	1.00	16.33

All models included the same random effects (RE = (1|participant)).
K= number of fixed effect parameters; Y= Ventilation; Sex= Man, Woman; HG= Height gain (m); VO_2= $VO_{2\text{-}max}$ (mL/kg.min); S= Speed (km/h); TC= Cycle type (CC, EAC); St= number of stops; ΔAICc= difference in AICc between best model and other models; AICWt= probability (weight) that among the set of candidate models, this model is closest to the true underlying model; AICc CumWt= cumulative weights; ev.ratio: evidence ratio = ratio of weights between best model and other models.

Table A.2
Overview of the best fit models predicting ventilation *with variables for route planners* with different fixed effects

	Model formula (in lme4 syntax)	K	AICc	ΔAICc	AICcWt	AICcWt CumWt	ev. Ratio
1	Y ~ Sex + HG + TC + S	7	520.98	0.00	0.50	0.50	1.00
2	Y ~ Sex + HG + TC + S + St	8	522.76	1.78	0.21	0.71	2.38
3	Y ~ Sex + TC + S	6	523.61	2.63	0.13	0.84	3.85
4	Y ~ Sex + TC + S + St	7	525.42	4.44	0.05	0.90	10.00
5	Y ~ Sex + HG + TC + St	7	525.76	4.79	0.05	0.94	10.00

All models included the same random effects (RE = (1|participant)).
K= number of fixed effect parameters; Y= Ventilation; Sex= Man, Woman; HG= Height gain (m); VO_2= $VO_{2\text{-}max}$ (mL/kg.min); S= Speed (km/h); TC= Cycle type (CC, EAC); St= number of stops; ΔAICc= difference in AICc between best model and other models; AICWt= probability (weight) that among the set of candidate models, this model is closest to the true underlying model; AICc CumWt= cumulative weights; ev.ratio: evidence ratio = ratio of weights between best model and other models.

Table A.3
Overview of the best fit models predicting bc_dose/km with different fixed effects

	Model formula (in lme4 syntax)	K	AICc	ΔAICc	AICcWt	AICcWt CumWt	ev. Ratio
1	Y ~ Sex + HG + TC + S	7	−228.56	0.00	0.46	0.46	1.00
2	Y ~ Sex + HG + TC + S + St	8	−226.85	1.71	0.20	0.65	2.30
3	Y ~ Sex + HG + TC + S + VO2	8	−226.10	2.46	0.13	0.79	3.54
4	Y ~ Sex + HG + TC + S + St + VO2	9	−224.36	4.20	0.06	0.85	7.67
5	Y ~ Sex + TC + S + VO2	7	−224.09	4.47	0.05	0.89	9.20

All models included the same random effects (RE = (1|participant)).
K= number of fixed effect parameters; Y= Ventilation; Sex= Man, Woman; HG= Height gain (m); VO2= $VO_{2\text{-}max}$ (mL/kg.min); S= Speed (km/h); TC= Cycle type (CC, EAC); St= number of stops; ΔAICc= difference in AICc between best model and other models; AICWt= probability (weight) that among the set of candidate models, this model is closest to the true underlying model; AICc CumWt= cumulative weights; ev.ratio: evidence ratio = ratio of weights between best model and other models.

Table A.4
Overview of the best fit models predicting bc_dose/Min with different fixed effects

	Model formula (in lme4 syntax)	K	AICc	ΔAICc	AICcWt	AICcWt CumWt	ev. Ratio
1	Y ~ Sex + HG + TC + S	7	−425.44	0.00	0.55	0.55	1.00
2	Y ~ Sex + HG + TC + S + St	8	−423.07	2.37	0.17	0.71	3.24
3	Y ~ Sex + HG + TC + S + VO2	8	−422.95	2.49	0.16	0.87	3.44
4	Y ~ Sex + HG + TC + S + St + VO2	9	−420.52	4.92	0.05	0.92	11.00
5	Y ~ Sex + HG + TC + St	7	−419.34	6.10	0.03	0.94	18.33

All models included the same random effects (RE = (1|participant)).
K= number of fixed effect parameters; Y= Ventilation; Sex= Man, Woman; HG= Height gain (m); VO2= $VO_{2\text{-}max}$ (mL/kg.min); S= Speed (km/h); TC= Cycle type (CC, EAC); St= number of stops; ΔAICc= difference in AICc between best model and other models; AICWt= probability (weight) that

among the set of candidate models, this model is closest to the true underlying model; AICc CumWt= cumulative weights; ev.ratio: evidence ratio = ratio of weights between best model and other models.

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