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Cycle-network expansion plan in Oslo: Modeling cost-effectiveness analysis and health equity impact

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Abstract
Physical inactivity is the leading cause of non-communicable diseases, and further research on the cost-effectiveness of interventions that target inactivity is warranted. Socioeconomic status is vital in this process. We aim to evaluate the cost-effectiveness of a cycle-network expansion plan in Oslo compared to the status quo by income quintiles. We applied a Markov model using a public payer perspective. Health outcomes were measured by quality-adjusted life years (QALYs) gained from the prevention of coronary heart disease, stroke, type 2 diabetes, and cancer. We measured equity impact by the concentration index and social welfare using the achievement index. We conducted sensitivity analyses. The intervention was generally more costly and more effective than the status quo. Incremental cost per QALY falls with income quintile, ranging from $10,098 in the richest quintile to $23,053 per QALY gained in the poorest quintile. The base-case intervention increased health inequality. However, a scenario targeting low-income quintiles reduced inequality and increased social welfare. In conclusion, the cycle-network expansion is likely to be cost-effective, but with equity concerns. If decision makers care about health inequalities, the disadvantaged groups could be targeted to produce more equitable and socially desirable outcomes instead of a uniform intervention across income quintiles.

KEYWORDS
cost-effectiveness analysis, cycling, equity, non-communicable diseases, physical activity, QALY

1 | INTRODUCTION

The global prevalence of insufficient physical activity is high, with higher rates in high-income Western countries (Guthold et al., 2018), and it is believed to incur a considerable economic burden. For instance, health care costs associated with inactivity have been estimated at $53.8 billion globally and $11.7 billion in Europe in 2013 (Ding et al., 2016). This estimate includes only the costs of treating five major non-communicable diseases (NCDs) related to physical activity, such as coronary heart disease (CHD), strokes, type 2 diabetes (T2D), breast cancer, and colon cancer. Thus, the incorporation of more physical activity into everyday life has substantial potential for improving health and reducing costs. Achieving this objective likely requires environmental, social, cultural and behavioral approaches (Sallis et al., 2006). Active modes of transportation, such as walking and cycling, have been recognized as possible avenues to increase physical activity levels through our daily routines (Goodman, 2013; Heath et al., 2012; Sahlqvist et al., 2012). In principle, walking and cycling provide substantial health and non-health benefits.

Furthermore, a growing body of literature indicates that cycling infrastructure not only increases the level of cycling in urban environments where motorized and active transport modes must co-exist, but also reduces motorized traffic emissions in urban areas (Götschi et al., 2015; Kriit et al., 2019; Mueller et al., 2018; Powell et al., 2010). However, investment in cycling infrastructure alone may not be sufficient by itself. Studies have highlighted the importance of integrated approaches, such as attitudinal and behavioral changes, conducive environments that encourage people of different socioeconomic statuses to cycle safely, and interventions that mitigate barriers to pursuing physical activity (Hafner et al., 2019). Thus, physical activity depends on either individual-level factors (such as age and gender) or on physical and environmental factors (like social and economic conditions) (Bauman et al., 2012). In many metropolitan areas, most of the people with low socioeconomic status live in economically disadvantaged areas with inadequate physical activity facilities, unsafe walking, and limited access to open green spaces (Hoffimann et al., 2017; Rawal et al., 2020). People with lower socioeconomic status are more likely to have inferior health and shorter life expectancies than their affluent counterparts (Althoff et al., 2017; Moore & Littlecott, 2015); this is attributed partly to physical inactivity (Cleland et al., 2012). Thus, understanding how the costs and the effects of an intervention distribute across different socioeconomic groups of society can contribute to evidence-based planning of public health programs. If the desired effects are more cost-effective, or if they are inequitably distributed, that knowledge is important both from a purely economic perspective and a distributional (e.g., prioritarian) vantage point.

Cycling has received increased attention as part of comprehensive and sustainable health, mobility, and environmental policies. Thus, the idea of considering investments in cycling as a measure of disease prevention and improving urban mobility has gained attention. For instance, investment in cycle infrastructure has been proposed as a strategy to increase cycling share in Oslo, Norway, to improve health and urban mobility (Oslo Municipality, 2018). A better understanding of the costs and effectiveness of cycling investments would be helpful to evaluate such initiatives. Although promoting cycling has moved up on the policy agenda in recent years, issues related to socioeconomic inequality in health are rarely explored empirically in cost-effectiveness analyses (CEAs) (Cookson et al., 2017). Recently, two methods have been developed to address equity issues in health economic evaluation: distributional CEA (Asaria et al., 2016) and extended cost-effectiveness analysis (ECEA) (Verguet et al., 2016). The former involves modeling and evaluating social distributions of health associated with an intervention, while the latter incorporates measures of financial risk protection and equity into standard CEA.

The ECEA builds on a standard CEA and considers three dimensions: health policy assessment, financial risk protection, and income distributional consequences (Verguet et al., 2016; Verguet et al., 2015). In Norway, health care services are publicly financed, and policies have little direct financial implications on private health expenditures. Thus, we emphasize the last dimension in this study, that is, distributional consequences across income quintiles. ECEAs have been applied in other public health interventions, such as tuberculosis, malaria, and different forms of vaccine (Johansson et al., 2015; Verguet et al., 2013), particularly in low-income countries. Although the cost-effectiveness of active travel (e.g., walking and cycling) has been widely researched using the standard approach, to our knowledge, this is the first study to explore the equity issue by applying the distributional consequences across income strata.

Thus, the aim of this study is to examine the cost-effectiveness of cycle-network expansions across income quintiles. The analysis emphasizes on a cycle-network investment plan as a means to increase physical activity in Oslo city by addressing the issue of equity (i.e., exploring CEAs in different income quintiles).

2 | METHODS

2.1 | Model structure

A probabilistic state-transition Markov model was developed to simulate a cohort of disease-free adults by socioeconomic status (measured by household income). We modeled the risk of four physical activity-related diseases (cancer, CHD, stroke, and T2D) over 40 years, and the associated costs and quality-adjusted life years (QALYs) change. The choice of the four disease conditions was based on sufficient evidence of a significant association between physical activity and risk for these diseases (Kyu et al., 2016; Pandey et al., 2015; Smith et al., 2016; Wahid et al., 2016). The model design was based on a previously published study that assessed the cost-effectiveness of cycle-network investments as a means of promoting physical activity (Lamu et al., 2020). Data to estimate the model's parameters for morbidity, mortality, physical activity levels, effectiveness, and costs were derived from various sources (details below).

2.1.1 | Model cohort

Healthy adults aged 30 and above entered the model. The starting age was set to 30 years because of the low risk of chronic conditions prior to the age 30 and the paucity of data on younger age groups (Lamu et al., 2020). The model has two arms: *status quo* (no intervention) and *cycle-network investments* (intervention arm). Based on data on the current cycling status in the Norwegian population, the cohort is grouped into two in both arms: *cyclists* and *non-cyclists*. In both arms, those who cycled were assumed to be *active*. However, a portion of the non-cyclists are assumed *active* elsewhere, while the rest are considered *insufficiently active* (hereafter *inactive*). Based on a study from seven European cities on European cyclists' behaviors, 28.6% of non-cyclists were active and achieved a recommended physical activity level (i.e., at least 30 min of moderate daily physical activity) (Raser et al., 2018). The intervention is assumed to increase cycling compared to the status quo from the first model cycle. In subsequent years, cohort members transition to another, or remain in the same, Markov state according to the transition probabilities. These transition probabilities are conditional on age, household income, and physical activity status. The effect of the intervention is thus indirect and impacts on costs and QALYs through increased physical activity.

2.1.2 | Health states

Given the structural similarities of each quintile, Figure 1 depicts the Markov model structure for the combined quintiles. Initially, the model starts from the "Well" state, where all individuals are considered disease-free. For each model cycle, an individual transition between model states according to the transition probabilities. Thus, individuals can stay in the "Well" state, or transition to any of the *disease* states or the "Dead" state. The transition probabilities are conditional on age, active status, and income quintile (measured by household income). In the model, the health states were assumed to be mutually exclusive, and there were no inter-disease state transitions.

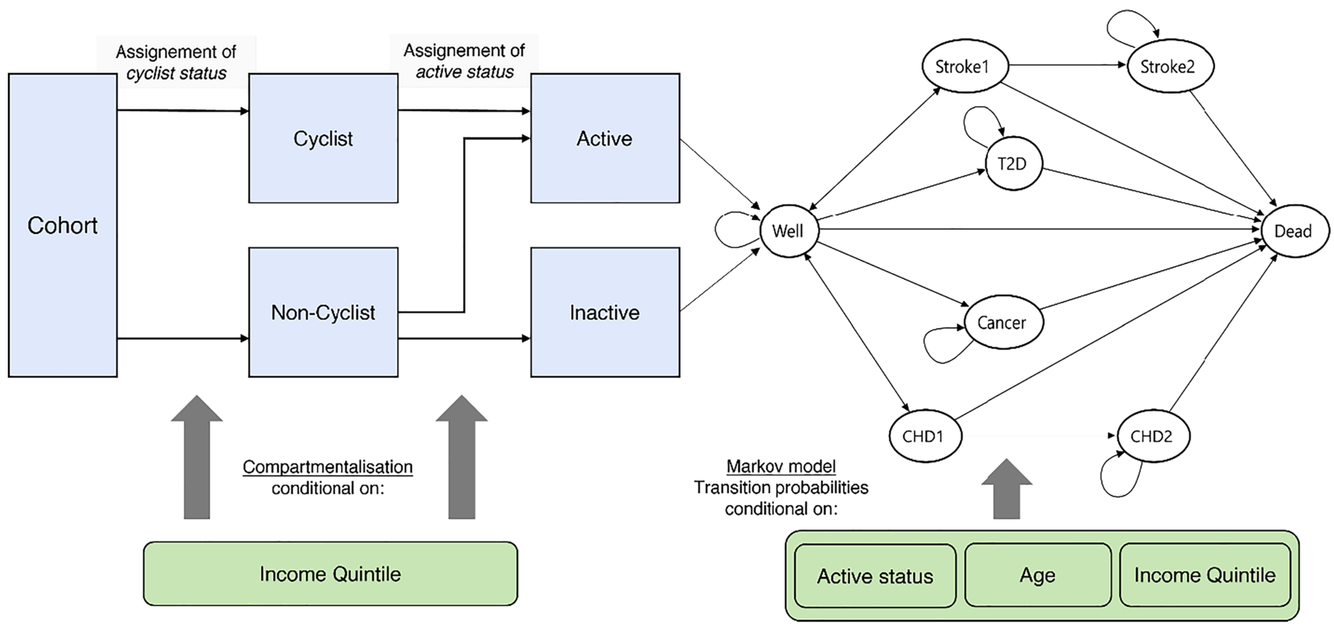

FIGURE 1 Conceptual illustration of dependencies for assignment of "active" status via cycling probability and the Markov state model

2.1.3 | Time horizon and discounting

Unless some special circumstances exist, the analysis period for infrastructural intervention (including cycle infrastructure investment) should coincide with the life of the project, which is set to 40 years (Norwegian Public Roads Administration, 2021). Thus, the time horizon of the model is set to 40 years in the base-case analysis, that is, the model follows the cohort of 30 years old until they reach 70 years. In the scenario analysis, a lifetime horizon would be considered, where the time horizon of 100 years was assumed. Future costs and QALYs were discounted at 4%, as recommended by the Norwegian Ministry of Finance (Official Norwegian Reports, 2012).

2.2 | Model inputs

2.2.1 | Disease and mortality transition probabilities

Age-specific incidence rates for all conditions, except for cancer, were retrieved from the most recent Global Burden of Disease (GBD) database for the Norwegian population (Global Burden of Disease Collaborative Network [GBD-CN], 2020). We obtained the incidence rates for cancer from the cancer registry statistics bank (Cancer Registry of Norway [CRN], 2020). Because incidence rates by income quintile were not available, we adjusted the age-specific incidence rates by the *incidence rate ratios* for each income quintile derived from published studies (Clegg et al., 2009; Li et al., 2008; Lysy et al., 2013; Petrelli et al., 2006). The incidence rate ratios were estimated by dividing the incidence rate in each income quintile by their average. We next estimated the age-specific incidence rates among *inactive* individuals by multiplying the adjusted age-specific incidence rates in the general population by the fraction of the disease incidences attributable to physical inactivity (Bolin, 2018; Brenner et al., 2017). Due to lack of data, population attributable fractions were assumed fixed across income quintiles. Appendix Table S1 in Supporting Information S1 provides the transition probabilities by income quintile for the inactive group. We estimated the transition probabilities for each condition among *active* individuals in the cohort by multiplying the probabilities of the *inactive* population with the relative risks of being active (Celis-Morales et al., 2017; Wahid et al., 2016). The relative risk of cancer incidence from active commuting was obtained by the weighted average of walking, cycling, and mixed mode commuting reported in a prospective cohort study by Celis-Morales et al. (2017). Table 1 summarizes the relative risk of active versus inactive.

Age-specific all-cause mortality rates were taken from the most recent GBD for the Norwegian population (GBD-CN, 2020). We divided mortality into two categories: mortality from the four diseases included in the model and background mortality. Background mortality is all-cause mortality excluding the mortalities attributable to the four conditions included in the model. As these mortality rates were not available for each income quintile, we estimated quintile-specific all-cause mortality and background mortality rates by the *mortality rate ratios* for each income quintile derived from the literature (Marshall-Catlin et al., 2019). The mortality rate ratio was given by the ratio of the mortality rate in each income quintile and their average value. Appendix Table S2 in Supporting Information S1 presents background and all-cause mortality rates.

In the model, we assumed that a given proportion of CHD and stroke events would be fatal and that people who survived these events had an increased subsequent risk of death. Due to the lack of Norwegian-specific data, case fatality rates for CHD and stroke were taken from a published population study in Sweden (Wilhelmsen et al., 2005), and assumed equal across income quintiles. Based on standardized mortality ratios reported in the Danish long-term follow-up studies of first-ever stroke patients (Bronnum-Hansen et al., 2001), an increase in the risk of death after the first year was applied to the all-cause mortality rates to reflect the higher post-stroke mortality. Annual mortality rates following the first CHD event were assumed to be like that of a stroke due to lack of information. Individuals in the non-fatal CHD or stroke state either remain in that state or fully recover or move to the “Dead” state. The probability of fully recovering after stroke was assumed to be 10% (American Stroke Association, 2019). Due to lack of data, the same probability was considered for the full recovery from CHD. Individuals with T2D were also assigned an increased risk of mortality using data from published literature (Preis et al., 2009). Similarly, individuals with cancer were assigned an increased risk of mortality using data from a Finnish population-based registry study (Kero et al., 2015). We assumed that individuals with T2D and cancer either stay in their states or die in subsequent cycles. We conservatively assumed that the model emphasizes the primary prevention of disease events, that is, the mortality risks from the diseases included in the model were assumed to be independent of physical activity. Table 1 summarizes case-fatality rates and relative risks of mortality from the diseases included in the model.

TABLE 1 Case-fatality rates, relative risks of disease events and relative risks of mortality for the diseases included in the model

	Base value	Lower	Upper	Source
CHD case-fatality rate				Wilhelmsen et al. (2005)
≤44	0.221	0.171	0.262	
45–54	0.217	0.168	0.258	
55–64	0.277	0.216	0.327	
65–74	0.353	0.278	0.411	
75+	0.429	0.343	0.495	
Stroke case-fatality rate				Wilhelmsen et al. (2005)
≤44	0.131	0.100	0.157	
45–54	0.122	0.093	0.146	
55–64	0.126	0.096	0.152	
65–74	0.165	0.126	0.197	
75+	0.244	0.189	0.289	
RR of conditions (active vs. inactive)				
Cancer	0.85	0.74	0.98	Celis-Morales et al. (2017)
CHD	0.80	0.75	0.86	
Stroke	0.82	0.77	0.87	
T2D	0.74	0.72	0.77	
RR of total mortality after diseases				
Cancer	4.20	4.00	4.30	Kero et al. (2015)
CHD	2.72	2.55	2.90	Bronnum-Hansen et al. (2001)
Stroke	2.72	2.55	2.90	Bronnum-Hansen et al. (2001)
T2D	1.95	1.64	2.33	Preis et al. (2009)

Abbreviations: CHD, coronary heart disease; RR, relative risk; T2D, type 2 diabetes.

2.2.2 | Cycle-network expansions and probability of cycling

The Oslo municipality has an ambitious plan to expand a network of cycle infrastructure in two phases. In Phase I, 100 km of cycle networks are to be built by 2025 (Oslo Municipality, 2018). In this study, we estimate the cost-effectiveness of this cycling infrastructure investment plan.

We estimated baseline probability of cycling using data from the Norwegian National Travel Survey 2019.[1] This survey contains a variable on cycle use that records the respondents' answer to the question "*How often do you use a cycle for daily activities at this time of the year?*" on six response levels: *1* (*Cycle almost every day, i.e., 5 to 7 times a week*) to *6* (*Never*). We dichotomized this variable by conservatively assuming that respondents who reported using a cycle 5 to 7 times a week as *active cyclists* (and the rest considered *insufficiently active*). Thus, the aim is to estimate the predicted probability of a positive outcome (i.e., being active) for each income quintile using (binary) logistic regression. Following the model's starting age of the cohort, our target population of interest is Oslo's population of adults aged 30+ years. The outcome variable is an indicator variable defined as cycling almost every day (5 to 7 times a week) versus <5 times a week. The exposure, household income quintile, was derived from the national household income deciles and given as (in thousands of Norwegian kroner [NOK]): quintile 1 = 350 and below, quintile 2 = 351–550, quintile 3 = 551–812, quintile 4 = 813–1194 and quintile 5 = 1194+ (Statistics Norway [SSB], 2019). In our logistic regression model, we adjusted for major confounding factors, such as sex (0 = female, 1 = male), age (continuous variable), cycling season (dichotomized into winter and non-winter months, i.e., 0 = Nov–Feb, 1 = Mar–Oct), and area dummy indicating residence in Oslo municipality. After excluding observations with missing information, a sample size of 24,468 was retained. Eventually, we estimated the adjusted predicted probability for each quintile by holding the value of residence area and seasons at 1 and considering a weighted average over the distribution of the other confounders.

Using information on cycling mode shares and cycling network's length from major European cities, a previous study estimated an absolute increase in the share of cycling by 3% associated with a 100 km increase in cycle-network's length as per Phase I of the cycle-network expansion plan in Oslo prior to adjusting for the baseline share of cycling (Lamu et al., 2020). Because of the lack of empirical data on the percentage increase in cycling trips associated with an additional cycle kilometer constructed in Norway, we used this 3% estimate to determine the probability of cycling after the intervention. This gives approximately a 25% relative increase in the probability of cycling from the status quo (no intervention) in the base-case analysis. Similarly, a cost-effectiveness study of cycle lane investment in New York City revealed that every additional one mile of cycle lane construction would increase the probability of cycle ridership by 0.4% (Gu et al., 2017), which is equivalent to a 25% increase in the probability of cycling per 100 km of cycle-network's construction. This is a crucial assumption in our analysis, and hence we explored alternative probabilities in the scenario analysis. Table 2 reports the resulting probabilities of cycling in the status quo and intervention.

2.2.3 | Costs

All costs were first inflated to July 2021 NOK, and then converted to US Dollar ($).[2] The intervention's costs and the annual per capita costs incurred by each condition were based on previously published studies (Lamu et al., 2020; Wisløff et al., 2008). First-year costs and subsequent-year costs were assigned for CHD and stroke of the health states modeled. Unit costs were assumed to be the same across income quintiles. Based on the Norwegian Public Roads Administration estimates for cycle-network construction in cities and dense areas, we applied an average cost of 25,000 NOK per meter (Espeland & Amundsen, 2012). After price adjustment and currency conversion, the construction cost was estimated at $3.5 million per km. An annual maintenance cost of 7% of the investment cost is also considered (Institute of Transport Economics, 2016). The investment cost was assumed to be a one-time initial cost in the intervention arm. Cost parameters are reported in Appendix Table S3 of Supporting Information S1.

2.2.4 | Health state utility values: Effectiveness

Effectiveness is measured in terms of QALYs that combine longevity (mortality) and health-related quality of life (morbidity) in a single metric and is a standard measurement of health outcomes across diverse programs and settings (Drummond et al., 2015). The EuroQol five-dimensional five-level (EQ-5D-5L) is the most widely used instrument in the measurement of QALYs. In our study, we estimated income-quintile-specific mean health state utilities for the included conditions using EQ-5D-5L from the multi-instrument comparison (MIC) survey. The MIC survey contains 7933 observations from six countries (Australia, Canada, Germany, Norway, the United Kingdom, and the United States) and includes a representative healthy group and seven disease groups (Richardson et al., 2012). As a Norwegian value set for the EQ-5D-5L is not presently available, we employed the recently published Danish EQ-5D-5L value set (Jensen et al., 2021) to measure QALY weights. In addition to EQ-5D-5L, the survey records several variables, including age, sex, and household income. Thus, a linear regression model was used—regressing EQ-5D-5L utilities against age, sex,

TABLE 2 Probabilities of cycling by income quintiles in the status quo and intervention

	Status quo[a]		Intervention[b]	
Quintile	Probability	SE	Probability	SE
1 (Lowest)	0.110	0.012	0.137	0.015
2	0.113	0.010	0.142	0.012
3	0.127	0.010	0.158	0.012
4	0.131	0.010	0.164	0.012
5 (Highest)	0.180	0.011	0.225	0.014
Average	0.132	0.010	0.165	0.013

Abbreviation: SE, standard error.

[a]Estimated based on 2019 National Travel Survey using binary logistic regression (5 to 7 times cycle use a week is assumed as being active).

[b]A 25% increase in the probability of cycling from the status quo is assumed for the base-case analysis.

country, disease conditions, and income quintile—to predict quintile-specific mean utility for each condition for the Norwegian population at the mean age of the cohort. The utilities for the "Well" (disease-free) state were estimated by the mean EQ-5D-5L of the *healthy* group stratified by income quintile. The utilities (by income quintile) for different health states are given in Appendix Table S3 of Supporting Information S1. Utilities associated with fatal CHD and stroke were obtained from literature (De Smedt et al., 2012; Verhaeghe et al., 2014). In addition, we assumed a 0.05 QALY gain per year due to improvement in wellbeing owing to physical activity (Beale et al., 2007; Lamu et al., 2020).

2.3 | Cost-effectiveness analysis

The analysis was performed from a public payer perspective that incorporates cycle infrastructure investments and future health care costs. The cost-effectiveness ratio for the intervention compared with status quo or "no intervention" was estimated using a Markov state model. The incremental cost per QALY, or incremental cost-effectiveness ratio (ICER), is estimated as the ratio of the net expected cost of the intervention and the net expected QALY gain, both relative to the status quo alternative in each income quintile.

2.4 | Sensitivity and scenario analyses

We performed one-way deterministic sensitivity analyses to assess the effects of uncertainty in major input parameters. Further, we conducted scenario analyses by altering the intervention's impact on the quintile-wise probability of cycling and varying the time horizon. For the intervention's impact on the probability of cycling, we considered three scenarios: scenario 1 is a 15% increase, scenario 2 is a 35% increase from the status quo, and scenario 3 relaxes the fixed relative increase (25%) in the probability of cycling in the base-case analysis. Consistent with the observed gradient of baseline rates, it is plausible that the effect of cycling infrastructure investment in wealthier areas may be higher. Thus, instead of a fixed 25% probability, we applied different rates for each income quintile in scenario 3: 20% in quintile 1, 22% in quintile 2, 25% in quintile 3, 28% in quintile 4, and 30% in quintile 5.[3] Due to lack of concrete evidence as to the direction of this change, we also conducted an opposite analysis to scenario 3. Because incidence of the diseases and mortality increase with age, we considered a longer time horizon (lifetime perspective) in the scenario analysis to capture QALYs gained from delayed deaths due to the intervention (Siebert et al., 2012). Thus, the model projects the lifetime effect using a time horizon of 100 years in the fourth scenario. While discounting future costs in economic evaluations is currently uncontroversial, there is no consensus on discounting future health benefits (Attema et al., 2018; Solberg et al., 2020). Thus, we have undertaken a fifth scenario without discounting for future QALY changes.

In the base-case analysis, we did not discriminate the intervention of cycle expansion plan across income quintiles (hereafter referred to as *untargeted intervention*), which was expected to increase health inequality. Thus, we simulated an alternative scenario in which the intervention could target the lower income quintiles, which we call *targeted intervention* to distinguish from the base-case (untargeted) intervention. In Oslo, as in most metropolitan areas, low socioeconomic status is concentrated in certain geographical areas, so that such a directed infrastructure policy is conceivable. In the targeted intervention, we considered an intervention that increased the expansion of cycle networks by twofold for the two lowest quintiles, maintained the base-case values for the third quintile, and no expansion plan for quintiles 4 and 5, while holding investment costs at the base-case values. For the sake of simplicity, we also assume a linear relationship between the cycling expansion and the corresponding increase in the probabilities of cycling; other inputs remain the same.

In the targeted intervention, we primarily intended to explore the impact of the policy intervention on (i) health inequality, measured by the standard concentration index (CI) for QALYs; and (ii) social welfare, measured by the health achievement index (HAI). Given the individual-level data on QALY gains, the CI that ranges from 0 to 1, 0 representing perfect equality and 1 perfect inequality (Kakwani et al., 1997), can be calculated as:

$$\mathrm{CI} = \frac{2}{n\mu}\sum_{i=1}^{n} H_i R_i - 1$$

where n is the number of individuals ranked according to their QALY gains beginning with the worst health, H_i is QALY gains for individual i, μ is the mean level of QALY gains, and R_i is the fractional rank in the income distribution of the ith individual. The HAI combines the average level of health and the inequality in health between the worse-off and better-off in a single metric and is a narrow measure of social welfare in the health domain (Cookson et al., 2020;

Wagstaff, 2002). The measure of HAI proposed by Wagstaff (2002) is given by one minus the inequality index times mean health. That is, $\mathrm{HAI} = \left(1 - \mathrm{CI}\right)\mu$.

The Markov model was developed and implemented with the TreeAge Software (©TreeAge Pro 2020 [v2.1]), while other analyses were conducted using Excel, Stata ® ver. 16.1 (StataCorp Station), and R (ver. 4.0.2).

3 | RESULTS

3.1 | Base-case CEA

Base-case incremental costs, incremental QALYs, and incremental costs per QALY are presented in Table 3 for each income quintile. Overall, both incremental costs and QALYs were positive, implying that the intervention is more costly but effective. While incremental costs exhibit no substantial difference across income quintiles, incremental QALYs rise with income. Thus, the intervention is modeled as being generally more effective among richer individuals than among their poorer counterparts. The cost-effectiveness ratios ranged between $10,098 and $23,053 per QALY gained, and for all groups, the intervention can be considered cost-effective. The lowest ICER was observed in the highest income quintile, whilst the lowest quintile produced the highest ICER. Over 40 years, the cycle-network expansion program, on average, is associated with approximately $437 in increased costs and 0.026 QALYs gained. For all groups, on average, the resulting ICER of the cycling expansion program relative to status quo was $16,575 per QALY gained.

3.2 | Scenario and sensitivity analyses

Table 4 reports the effects of alternative scenario analyses on cost-effectiveness results for the intervention compared to the status quo. The probability of cycling after the cycle-network expansion had the most significant impact on ICERs. For instance, an increase in probability of cycling by 35% reduced ICERs by 31.9% in the first quintile and 36.8% in the fifth quintile in favor of the cycle-network expansion program. Compared to the base-case fixed rate of 25% of cycling across income quintile, the increasing rate (Scenario 3) produced a similar conclusion: the investment is highly cost-effective among the affluent than the deprived. However, the third scenario further widened the difference in the ICERs among different income groups: the investment becomes even less cost-effective in the first two quintiles, while it is more cost-effective in the last two quintiles. The opposite of scenario 3 (decreasing rate of cycling by income, results not reported here) significantly reduce this gap: the ICERs are quite similar across quintiles, except in the highest income group (quintile 5), where ICER is quite small. The expansion program would also be more cost-effective with longer analytical horizons. Figure 2 depicted quintile-specific cumulative QALYs in the status quo (no intervention), base-case (untargeted) analysis and targeted intervention. In the targeted intervention, cumulative QALYs are higher in the lowest two quintiles, while keeping health at the status quo for the two highest quintiles. Thus, health inequality is less in the targeted compared to untargeted intervention.

Figure 3 depicts health inequality and social welfare in the status quo (no intervention), base-case (untargeted) intervention, and in the targeted intervention. Note that the untargeted intervention increases health inequality. The targeted intervention produced the lowest health inequality. For instance, the CI significantly dropped from 0.0125 in the base-case (untargeted) intervention to 0.0118 in the targeted intervention ($p < 0.001$). Similarly, the targeted intervention

TABLE 3 Base-case cost-effectiveness results by income quintile

	Status quo		Intervention		Incremental		
	Cost ($)	QALY	Cost ($)	QALY	ΔCost ($)	ΔQALY	ICER
Quintile 1	27,525	17.371	27,997	17.391	472	0.020	23,053
Quintile 2	27,851	17.659	28,304	17.681	454	0.021	21,151
Quintile 3	26,823	18.101	27,281	18.127	458	0.026	17,788
Quintile 4	25,695	18.197	26,106	18.223	412	0.026	15,991
Quintile 5	24,382	18.488	24,770	18.526	387	0.038	10,098
Average	26,455	17.909	26,892	17.936	437	0.026	16,575

Abbreviations: ICER, incremental cost-effectiveness ratio; QALY, quality-adjusted life year.

TABLE 4 Cost-effectiveness results by income quintile: Scenario analyses

	Status quo		Intervention		Incremental		
Quintiles	Cost ($)	QALY	Cost ($)	QALY	ΔCost ($)	ΔQALY	ICER
Scenario 1 (15% increase in the probability of cycling)							
Quintile 1	27,525	17.371	28,000	17.381	475	0.010	46,801
Quintile 2	27,851	17.659	28,304	17.672	454	0.013	35,727
Quintile 3	26,823	18.105	27,323	18.120	500	0.015	32,544
Quintile 4	25,695	18.197	26,132	18.212	438	0.015	28,340
Quintile 5	24,382	18.488	24,804	18.511	422	0.023	18,600
Average	26,455	17.909	26,913	17.925	458	0.015	30,001
Scenario 2 (35% increase in the probability of cycling)							
Quintile 1	27,525	17.371	27,969	17.399	444	0.028	15,690
Quintile 2	27,851	17.659	28,275	17.690	424	0.031	13,805
Quintile 3	26,823	18.105	27,255	18.139	432	0.034	12,709
Quintile 4	25,695	18.197	26,076	18.232	381	0.035	10,873
Quintile 5	24,382	18.488	24,701	18.538	319	0.050	6384
Average	26,455	17.909	26,855	17.945	400	0.036	11,242
Scenario 3 (increase in probability of cycling with income)							
Quintile 1	27,525	17.371	27,983	17.386	457	0.015	29,927
Quintile 2	27,851	17.661	28,311	17.680	461	0.019	24,020
Quintile 3	26,823	18.101	27,281	18.127	458	0.026	17,788
Quintile 4	25,695	18.197	26,089	18.225	394	0.028	13,946
Quintile 5	24,382	18.488	24,733	18.531	351	0.043	8101
Average	26,455	17.964	26,879	17.990	424	0.026	18,757
Scenario 4 (lifetime perspective, 100 years' time horizon)							
Quintile 1	35,111	18.447	35,580	18.470	469	0.023	20,412
Quintile 2	36,902	18.917	37,344	18.941	442	0.025	18,042
Quintile 3	36,441	19.513	36,874	19.544	433	0.031	14,163
Quintile 4	35,804	19.722	36,183	19.754	379	0.033	11,632
Quintile 5	35,017	20.165	35,365	20.211	348	0.047	7463
Average	35,855	19.295	36,269	19.327	414	0.031	13,182
Scenario 5 (no discounting of future QALY)							
Quintile 1	27,525	33.527	27,997	33.569	472	0.042	11,301
Quintile 2	27,851	34.293	28,304	34.336	454	0.043	10,481
Quintile 3	26,823	35.300	27,281	35.352	458	0.052	8815
Quintile 4	25,695	35.562	26,106	35.615	412	0.054	7690
Quintile 5	24,382	36.209	24,770	36.285	387	0.077	5045
Average	26,455	34.877	26,892	34.930	437	0.053	8172

Note: Scenario 1: 15% increase in probability of cycling from the status quo; scenario 2: 35% increase in the probability of cycling; scenario 3: Increasing rate of cycling (20% in Quintile 1, 22% in Quintile 2, 25% in Quintile 3, 28% in Quintile 4, and 30% in Quintile 5) instead of the base-case fixed rate of 25% across income quintiles; scenario 4: Lifetime time horizon (set to 100 years); and scenario 5: No discounting for future benefits.

Abbreviations: ICER, incremental cost-effectiveness ratio; QALY, quality-adjusted life year.

produced higher overall social welfare (as measured by HAI) compared to the base-case or untargeted intervention. Thus, the QALY distribution of the inequality-reducing scenario is not only less unequal than that of the base-case or untargeted intervention, but also clearly preferable from a social welfare perspective.

Appendix Table S4 in Supporting Information S1 presents the effects of a series of one-way sensitivity analyses on ICERs for each quintile. The wellbeing gains due to physical activity had the most significant impact on ICERs, followed

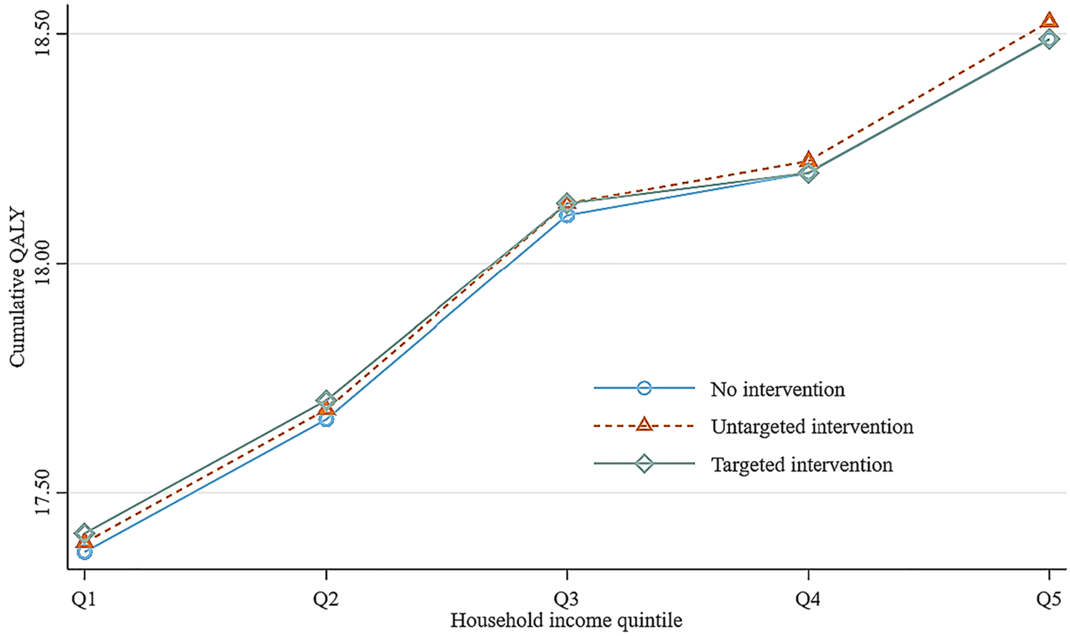

FIGURE 2 Cumulative quality-adjusted life years (QALYs) compared: No intervention, untargeted intervention, and targeted intervention. Targeted intervention involves increasing cycle expansion by two-fold for quintiles 1 and 2, maintaining base-case analysis for quintile 3, and no intervention for quintiles 4 and 5. Q1, the lowest income quintile; Q5, the highest income quintile

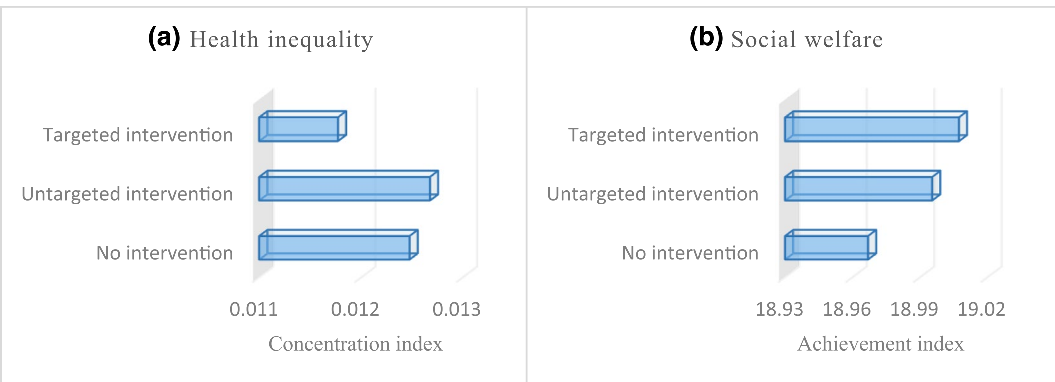

FIGURE 3 Discriminating cycle expansion plan across income quintiles: health inequality and social welfare impact. No intervention: status quo (no new cycle infrastructure investment); targeted intervention: inequality-reducing policy that involves increasing cycle expansion by two-fold for quintiles 1 and 2, maintaining the base-case analysis for quintile 3, and no intervention for quintiles 4 and 5; Untargeted intervention: base-case cycle expansion plan (Table 3)

by the cost of intervention. For instance, if the wellbeing gains due to physical activity decreased by 25% (from initial value of 0.05), the ICER would increase by 27.9% in quintile 1 and 31.2% in quintile 5 compared to the base-case ICER values. Starting age, discount rate for future benefits and the baseline probability of cycling were also influential. The results are generally less influenced by variations in other key parameters. Overall, the cycle-network expansion plan would be cost-effective at a threshold of below $30,000 per QALY gained.

4 | DISCUSSION

In this study, we evaluated the long-term cost-effectiveness of cycle-network investment compared to the status quo by income quintile. The intervention was more effective and more costly than the status quo, resulting in ICER estimates that range from $10,098 to $23,053 per QALY gained. On average, our study suggests that cycle-network expansion would come at a cost of $16,575 per QALY gained. These results are clearly below the Norwegian cost-effectiveness threshold used for drug-reimbursement decisions.

The incremental cost per QALY generally falls with income quintile, where the highest incremental cost per QALY was observed in the lowest two quintiles. The incremental cost per QALY is clearly lower in the fifth quintile (the richest group). The incremental costs per QALY for the poorest is more than twice the richest group, indicating that the intervention is more cost-effective among the better-off than the poor. The results come from our modeling and input data, particularly the high probability of cycling among the richest individuals. For instance, the probability of cycling in the fifth quintile is two-thirds higher than in the first quintile. This could be attributable to better and easier access to safe cycling infrastructure in areas where people with high socioeconomic status live (Flanagan et al., 2016; Hosford & Winters, 2018). Based on the efficiency principle alone, this finding could support intervention in the high-income groups (i.e., more investment in a region where cycling infrastructure is already high). However, this would exacerbate the equity problem. That is, the least affluent members of the society receive a disproportionately smaller share of the increasing infrastructure. One important challenge is therefore how to balance the efficiency-equity trade-off. Alternative measures would be needed for trading off some health gain for broader distribution, which is often viewed as a desirable societal goal.

Although there is no consensus on how to develop health policy that maximizes health gains with fair distribution of resources, the World Health Organization recommends that equity and efficiency should simultaneously be the goals of the health care system (World Health Organization, 2008, 2014). This is also clearly stated in Norwegian health policy documents (Ministry of Health and Care Services [HOD], 2016; Official Norwegian Reports, 2014). Thus, there would be instances when interventions could improve either equity or efficiency. For instance, the targeted intervention (more cycling route expansion in some population groups, particularly disadvantaged groups) had reduced inequality in health while slightly reducing overall health (as measured by average QALYs) compared to the base-case values. Thus, the policy resulted in a trade-off between efficiency and equity, where it improved health equity and reduced total health (Cookson et al., 2020). Despite a slight reduction in overall health (measured by QALYs), there is an overall social welfare gain (measured by HAI) under the targeted intervention compared to the base-case (untargeted) analysis that treats all income groups equally. Thus, the targeted intervention was modeled as producing more equitable and socially desirable results, that is, it maximized equity-weighted benefits (Figure 3).

This study builds upon a previous study that assessed the cost-effectiveness of expanding cycle networks (Lamu et al., 2020). However, there are key differences between the two. First, unlike the previous one, the present study addressed the issue of equity by conducting a CEA across household income quintiles. Second, some key input parameters have also been modified and improved. For instance, the probabilities of cycling for the baseline analysis were calculated based on the Norwegian National Travel Survey 2019 for each income quintile in this analysis, whereas cycling mode share was applied in the previous study. Despite these differences, the findings of both studies were similar, that is, cycling-network expansions in big cities like Oslo is highly cost-effective.

Our findings are in line with previous studies evaluating the cost-effectiveness of infrastructure investment programs targeted to improve physical activity (Beale et al., 2012; Chapman et al., 2018; Gu et al., 2017), though none conducted cost-effectiveness by income strata. For example, an investment in environmental interventions to encourage physical activity in England appeared to be cost-effective, with ICERs ranging between £1884 (for five sessions of physical activity per week) and £9439 (for one session of physical activity per week) per QALY gained (Beale et al., 2012). Similarly, the Citi Bike expansion program relative to the status quo in New York City produced an ICER of $7869 per QALY gained. The ICER per QALY gained we found for the total population in the current study compares fairly with these estimates.

This study has several strengths. It employed a previously used Markov model (Lamu et al., 2020) and extended it with equity considerations by conducting CEAs across income quintiles. In several European countries (including Norway), a promising progress on policies promoting cycling expansion has been observed. The socioeconomic distribution of their effects on physical activity, and hence on the distribution of health, however, is unclear. This is the first empirical study that attempts to explore the cost-effectiveness of cycle infrastructure investment policies, taking equity considerations into account. Moreover, a series of sensitivity analyses and scenarios were conducted to explore the uncertainties in assumptions and parameters used in the model, and the analyses suggest that the results are robust to changes in various input parameters. Parameter estimates were also selected as much as possible from published meta-analyses to minimize biases.

In a cost-benefit analysis, often used in the transport sector, any health benefits of an intervention are measured in monetary terms (e.g., using a “value of statistical life”). The cost-benefit analysis is a more comprehensive approach since it monetizes all costs and benefits. However, this monetization process sometimes fails to address the need of policymakers. For instance, beyond economic efficiency, the current paper considered the issue of health inequality, which can arguably be better explored with distributional CEA where the health benefits are measured in terms of QALYs rather than monetary units (Cookson et al., 2020).

The study also has several limitations. The main limitation of the analysis relates to the availability and quality of evidence on the input parameters used in the model. For instance, the effectiveness evidence on cycling infrastructure interventions suggests an increase in the probability of cycling without much information on the intensity of cycling use both after the intervention and prior to the new facility being available. Such a lack of information on cycling intensity makes it difficult to generalize findings to areas of physical activity beyond cycling. Our model builds on the assumption that all cyclists are active, which may not always be true, as an increase in cycling cannot directly translate to being active (Lamu et al., 2020). Yet, our conclusion remains unchanged after relaxing this assumption in the deterministic sensitivity analysis. Another limitation could be the use of self-reported measures of cycling activity, which may bias our findings. However, a rudimentary validation of the quality of this variable against another variable on all trips made on the preceding day has shown good accuracy of the variable. For instance, for the group cycling 5–7 days of the week, at least $5/7 = 0.71$ should report one trip conducted by cycle on the previous day. The mean number of actual cycle trips on the preceding day for this group was 1.3, indicating a high face validity for this variable. Furthermore, the implicit assumption that the reported changes in cycling activities will be sustained in the long term can be questioned.

Regarding the modeled effect of the intervention on cycling behaviors, our analysis assumed a fixed and multiplicative effect; that is, the probability of cycling increases by 25% (from its baseline value) after the cycling infrastructure investment in each income quintile. This could be debated, as this rate might depend on the level of income. However, results from a sensitivity analysis that assumes higher effects among the affluent group is consistent with the base-case analysis; that is, the intervention is more effective among richer group. Our model is also based on the assumption that the cohort starts cycling at the age of 30 years, which may result in an underestimation of the potential benefits if, for instance, younger individuals benefit from the cycle expansion by becoming more physically active.

There are also uncertainties related to the estimation of costs. Some costs reported in the literature are inadequately presented and usually lack detail. For example, we are unable to find treatment costs of conditions included in the model separately for each income quintile. We assumed these costs are independent of income, and hence remain constant across income quintiles. This may not be the case, because treatment costs of the conditions included in the model could be greater for the high-risk group (low-income groups) compared to high-income groups. A related issue is the exclusion of indirect costs, or costs of production loss due to ill health. A twofold explanation for this would be: (1) a lack of evidence on such costs and (2) a lack of agreement in costing methods. Regarding the latter point, some argue that only costs due to time spent seeking and obtaining care should be considered, while productivity losses, such as absenteeism, should be excluded to avoid double counting because they are already captured in the QALY weights (Gold et al., 1996). Others argue that even the time spent seeking care does not result in any additional productivity loss because patients are already off work due to their illness, and hence not relevant (Drummond et al., 2015). Most importantly, the Norwegian guidelines on CEAs in health care discourage the inclusion of loss of production due to ill health (Ministry of Health and Care Services [HOD], 2016), and hence were not included in cost calculations in this study.

Another important point that needs to be considered is the equity implications of the findings. There is a concern that those accessing the service are usually the most affluent and that such interventions could even exacerbate inequalities. This could be particularly relevant to interventions such as cycle facilities, which may be positioned in more affluent areas of big cities and mostly accessible to wealthy individuals (Goodman, 2013; Sahlqvist et al., 2012). This issue could partly be addressed through the design and delivery of the interventions as well as subsidizing or even incentivizing access among the least affluent groups. One straightforward intervention design would be greater investment in cycling infrastructure in socioeconomically disadvantaged areas. Our targeted intervention scenario clearly demonstrated that prioritizing the low-income groups not only improves equity, but also increases the inequality-weighted overall health benefits of the population compared to the base-case or untargeted intervention, that is, the targeted intervention reduced health inequality and increased social welfare (as measured by HAI).

Despite these limitations, our study suggests that the cycle-network expansion program in Oslo city is likely to be highly cost-effective relative to no action. It would be reasonable for policymakers to expand cycle infrastructure and encourage cycle commuting, even with respect to the broader health benefits alone. Our results suggest that, if decision makers care about health inequalities and “leave no one behind,” they should make greater investment in cycling facilities in socioeconomically disadvantaged areas, which is more equitable and may also produce higher social welfare. Our findings provide support for concerns related to distributional inequalities in access to cycle infrastructure, suggesting the importance of considering the socioeconomic status factor in the cycle infrastructure planning and intervention process.

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CONFLICT OF INTEREST

None.

DATA AVAILABILITY STATEMENT

Some of the data that support the findings of this study are available from the corresponding author upon reasonable request. Other data that support the findings of this study are available from the Norwegian Public Roads Administration (NPRA). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of NPRA.

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ENDNOTES

[1] (Some of) the data applied in the analysis in this publication are based on "Norwegian National Travel Survey 2018-19". The survey was financed by Ministry of Transport and Communications, Norwegian Public Roads Administration, Norwegian National Rail Administration, The Norwegian Coastal Administration and Avinor. The data was collected by Epinion under the guidance of the Institute of Transport Economics and the Norwegian Public roads Administration. The data was made available by the Norwegian Public Road Administration. Neither Ministry of Transport and Communications, Norwegian Public Roads Administration, Norwegian National Rail Administration, the Norwegian Coastal Administration, Avinor, Epinion, nor the Institute of Transport Economics are responsible for the analyses/interpretation of the data presented here.

[2] Average exchange rate of 8.5 Norwegian kroner per $1 has been assumed (the average of monthly exchange rates: Jan.–Aug. 2021). https://www.valuta-kurser.no/en/norges-bank-monthly-average-2021-exchange-rate.

[3] Consistent with the observed gradient of base-case rates, we assumed smaller difference between the 1st two quintiles and the last two quintiles, while maintaining, on average, the base-case rate of 25%.

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