Promoting healthy populations as a pandemic preparedness strategy: a simulation study from Mexico

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Summary

Background The underlying health status of populations was a major determinant of the impact of the COVID-19 pandemic, particularly obesity prevalence. Mexico was one of the most severely affected countries during the COVID-19 pandemic and its obesity prevalence is among the highest in the world. It is unknown by how much the COVID-19 burden could have been reduced if systemic actions had been implemented to reduce excess weight in Mexico before the onset of the pandemic.

Methods Using a dynamic epidemic model based on nationwide data, we compare actual deaths with those under hypothetical scenarios assuming a lower body mass index in the Mexican population, as observed historically. We also model the number of deaths that would have been averted due to earlier implementation of front-of-pack warning labels or due to increases in taxes on sugar-sweetened beverages and non-essential high-energy foods in Mexico.

Findings We estimate that 52.5% (95% prediction interval (PI) 43.2, 61.6%) of COVID-19 deaths were attributable to obesity for adults aged 20–64 and 23.8% (95% PI 18.7, 29.1%) for those aged 65 and over. Had the population BMI distribution remained as it was in 2000, 2006, or 2012, COVID-19 deaths would have been reduced by an expected 20.6% (95% PI 16.9, 24.6%), 9.9% (95% PI 7.3, 12.9%), or 6.9% (95% PI 4.5, 9.5%), respectively. If the food-labelling intervention introduced in 2020 had been introduced in 2018, an expected 6.2% (95% PI 5.2, 7.3%) of COVID-19 deaths would have been averted. If taxes on sugar-sweetened beverages and high-energy foods had been doubled, trebled, or quadrupled in 2018, COVID-19 deaths would have been reduced by an expected 4.1% (95% PI 2.5, 5.7%), 7.9% (95% PI 4.9, 11.0%), or 11.6% (95% PI 7.3, 15.8%), respectively.

Interpretation Public health interventions targeting underlying population health, including non-communicable chronic diseases, is a promising line of action for pandemic preparedness that should be included in all pandemic plans.

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Keywords: Pandemic preparedness; Epidemic response plan; BMI; Obesity; COVID-19; Population health

Introduction

Pandemic preparedness plans describe the steps nations can take to reduce the likelihood of outbreaks of infectious disease and reduce the severity of such outbreaks, should an international sanitary emergency be declared.[1] Steps to limit severity focus on mitigation measures such as surveillance, test and trace, self-isolation, quarantining, and vaccination, and the health-system response and treatment capacity. However, other factors will modify the impact of a pandemic

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Research in context

Evidence before this study

We searched for publications in PubMed and SciELO databases from March 1, 2020 to May 15, 2023, with no language restrictions, using the search terms ("obesity" OR "overweight" OR "BMI") AND ("COVID-19" OR "SARS-CoV-2") AND ("death" OR "severity" OR "critical illness" OR "hospitalization" OR "severe"). We also reviewed the World Health Organization (WHO) documents: International Health Regulations, the pandemic Influenza preparedness plan, and the Health Emergency Preparedness, Response & Resilience. We found several systematic reviews and meta-analyses that report that obesity is associated with an increased risk of severe COVID-19 outcomes including hospitalisation, critical illness, and death. These studies are at high risk of bias, given that obesity is often self-reported and not well-defined. Several authors have proposed COVID-19 and obesity as a syndemic phenomenon leading to higher mortality rates in populations with higher BMI. However, it remains unknown how much less severe COVID-19 might have been had there been lower BMI levels, and whether obesity-reducing policies could be a tool to reduce Pandemic severity and deaths. Pandemic plans mainly focus on financing, governance, and system responses: in particular, on operations and interventions to attenuate transmission, and the capacity of the health system to care for patients. Most pandemic preparedness protocols do not consider improving population health among actions nations can take to prepare for future pandemics. The WHO is currently working on the Preparedness and Resilience for Emerging Threats initiative, which focuses on health systems and capacities specifically for respiratory pathogens, with no consideration of the underlying population health as a key factor for pandemic impact.

Added value of this study

We created an epidemiological simulation model that accounts for the interaction between non-communicable chronic diseases and infectious diseases. Our model showed that the implementation of structural interventions to reduce obesity and overweight on a population level could have reduced the impact of COVID-19 in Mexico, benefitting all people, including those without high BMI.

Implications of all the available evidence

Planning for preparedness to mitigate the impact of an epidemic tends to focus on the health system's capacity and direct actions to reduce the probability of infection, yet rarely considers indirect influences on the pandemic's severity, such as the underlying population health. Obesity prevalence was a major determinant of the severity of the COVID-19 pandemic and its reduction would have reduced the burden of severe COVID-19 outcomes. Improving population health through specific interventions should be integral to any pandemic preparedness plan, particularly for countries with a high toll of chronic diseases.

independently of the system response. In particular, the health status of the population, including the prevalence of non-communicable diseases,[2] prior to the emergence of a pandemic is a critical factor that needs to be considered as part of any comprehensive pandemic preparedness effort.

The underlying health status of the population, in particular obesity prevalence, was a major determinant of the impact of the COVID-19 pandemic. Obesity, defined as having a body mass index (BMI) of 30 kg/m^2 or higher, is associated with an increased risk of infection and with severe forms of COVID-19.[3–8] Over the last decades, Mexico experienced a substantial increase in obesity prevalence, from 23.5% in 2000 to 36.1% in 2018.[9] Mexico was also among the countries with highest COVID-19 mortality during the pandemic,[10] and it is estimated that 33.6% of deaths in the country were attributable to obesity, hypertension, and diabetes.[11]

Excess weight, in contrast to other risk factors for COVID-19, such as advanced age or being immunocompromised, is amenable to intervention. Timely implementation of interventions to reduce excess weight could have changed the landscape of the pandemic in countries with a high burden of obesity, such as Mexico. In the last decade, policies were introduced in Mexico to address the structural determinants of poor diets by steering consumers towards making choices that are better for their health. In 2014, the country introduced a 10% tax to industrialised sugar-sweetened beverages (SSB) to curb consumption.[12] Simultaneously, an 8% tax on non-essential high-energy foods was also implemented.[13] In 2020, a food-and-drink labelling regulation was introduced, mandating front-of-pack labelling to warn consumers if the product is high in calories, sugar, sodium, or fats.[14] A survey found that 44.8% of adults reported buying less unhealthy food because of front-of pack labelling, although the survey is not nationally representative.[15] Still, it is unknown whether an earlier implementation of these measures could have changed the COVID-19 epidemic impact in Mexico.

To contextualise the change in BMI in Mexico over the last twenty years and its impact on the severity of the COVID-19 pandemic in the country, we first aimed to demonstrate what would have happened if the BMI distribution had remained as it was in 2000, 2006, and 2012 (years for which survey data are available). These are meaningful scenarios for Mexico because they correspond to attainable population BMI distributions, as they have been observed historically. Then, to understand the potential impact of structural interventions to reduce body weight as a pandemic preparedness strategy in Mexico, we created scenarios to assess what would have happened if the introduction of front-of-pack warning labels or increases to the SSB and non-essential high-energy foods taxes had been implemented two years prior to the onset of the pandemic.

Methods

Our methodological approach is shown schematically in Fig. 1. We constructed a synthetic population of adults in Mexico, where each individual had a fixed age and sex, and a unique body mass index (BMI) value in each of nine different scenarios. In the reference scenario, the population had a BMI distribution drawn from the National Survey of Health and Nutrition (ENSANUT, for its Spanish acronym) survey conducted in 2018, corresponding to the last nationally representative survey before COVID-19.[9] We used anthropometric data with accompanying survey weights from 17,474 adults aged 20 and over. We used this population to create the other scenarios by sampling or altering BMI values to reflect the hypothetical population with reduced BMI (Supplementary Figure S4). The following scenarios were considered: the reference scenario (corresponding to what was observed); no obesity (all adults have BMI lower than 30 kg/m^2); historical BMI distributions (what if the BMI distribution had not changed since 2000, 2006, or 2012); labelling (what if food labels had been introduced in 2018); taxation (what if taxes had been doubled, trebled, or quadrupled in 2018).

Outcomes

For each scenario, we projected the number of COVID-19 infections, hospitalization days, and deaths from the beginning of January 2020 to the end of October 2021. We calculated the years of life lost (YLL) per death using life-expectancy values from 2019[16] for all scenarios, i.e., we did not adjust for changes to life expectancy as a consequence of changes to BMI.

BMI impact on COVID-19 dynamics

We modelled individual-level risks of COVID-19 outcomes based on each individual's age and scenario-specific BMI using published relative risk dose-response relationships.[8] We computed the population-average relative risks of disease outcomes by age group for each scenario from the synthetic population (Supplementary Table S7). We computed risks for three outcomes: positive diagnosis, hospitalisation, and death and mapped these relative risks onto the relevant parameters in the epidemic model (shown schematically in Supplementary Figure S5), which are probabilities of acquisition of infection, the infection-hospitalisation rate, and the infection-fatality rate (Fig. 2). Refer to the Supplementary Appendix A for details.

Statistical analysis

BMI reduction scenarios

No-obesity scenario. To construct the no-obesity scenario from the 2018 BMI distribution, we imputed values for BMI for all people with obesity from all people without obesity, matching by age and sex. Comparing outcomes for this population to those for the reference scenario allowed us to estimate transmission-model population-attributable fractions (PAF) of COVID-19 outcomes due to obesity. This contrasts with the conventional PAF calculation, in which the division of the population into those with and without the risk factor obscures the effect of the risk factor at the population level.[17]

Historical BMI distribution scenarios. We created three scenarios using past ENSANUT surveys,[18] asking what would have happened if the population had had the BMI distribution of 2000, 2006, or 2012 (average values shown in Supplementary Table S6). We sampled new values for BMI for all people from the historic survey data, matching by age and sex.

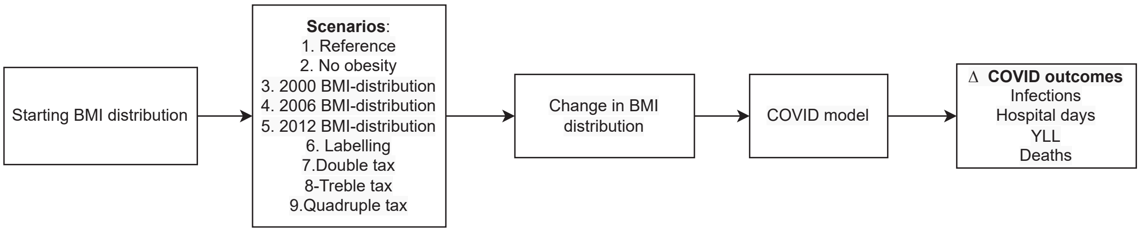

Fig. 1: **Summary of methods.** We started with the 2018 survey from ENSANUT, from which we computed each individual's BMI. We used this dataset to represent the reference scenario. We created new scenarios by adjusting individuals' BMI values according to the scenario. Using the new BMI distributions together with BMI dose-response relationships, we computed new disease-state transition rates for each age group in each scenario. We then simulated the COVID-19 epidemic using the population-average transition rates and compared epidemic outcomes to those seen in the reference scenario.

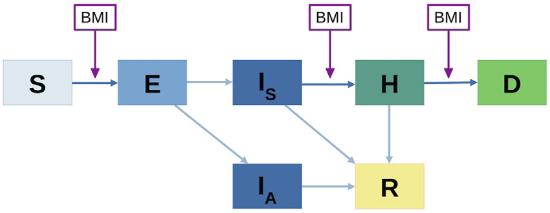

Fig. 2: **State transitions for the COVID-19 epidemic model.** Disease states are susceptible (S), exposed (E—infected but not yet infectious), symptomatic infectious (I_S), asymptomatic infectious (I_A), hospitalised (H), recovered (R), and deceased (D). In the model, BMI impacts three state transitions: from susceptible to exposed, from symptomatic to hospitalised, and from hospitalisation to death. NB: the model includes vaccination states for all compartments, not shown here. Refer to Supplementary Appendix E for details.

Labelling scenario. In our labelling scenario, we assumed that the labelling scheme launched in 2020 was instead launched in 2018. We estimated the caloric and sodium reduction by age group and BMI category, using the estimated change presented in Basto-Abreu et al.[14] (Supplementary Table S4). To estimate the consequent weight change, we used Hall's model[19] via the R package *bw*.[20] We assumed that the daily reduction in consumption was constant for two years up to the beginning of the pandemic, from which point BMI remained the same.

Tax scenarios. We created scenario populations corresponding to different levels of taxation, estimating the change in consumption by age group and BMI category using published estimates for the relationships between tax and purchases of SSB[12] and taxed food.[13] Reference consumption was taken from the ENSANUT 2018 food-frequency questionnaire. The current rate of tax in Mexico is 10% for SSB, and 8% for non-essential energy-dense foods. We considered that this rate was doubled, trebled, or quadrupled, two years before the onset of the pandemic. To create our scenario-specific synthetic populations, we assumed that daily caloric intake was reduced by fixed amounts by socioeconomic status per 10% tax on SSB[12] and 8% tax on non-essential energy-dense foods[13] for the two years preceding the pandemic. Reductions were allocated according to age group and BMI category (Supplementary Table S5). We assumed linear changes in consumption with respect to the tax rate,[21] and that products compositions did not vary as a result of the tax being implemented. We estimated weight changes in the same way as for the labelling scenario.

We used the compartmental epidemic model DAEDALUS,[22] described in Supplementary Appendix E, to simulate COVID-19 outcomes. In simulating scenarios, we assumed no changes in the transmission rate apart from the parameters we modified, i.e., we assumed that population behaviour and government response are the same in all scenarios as in the reference scenario. Assessments of vaccine impacts often rely on these assumptions,[23] leading to estimates that serve as upper bounds to the true number of cases, hospitalisations, and deaths that would have been averted. We additionally assumed no changes to BMI in the population over time and that transition rates remained the same for the duration of the epidemic simulation. That is, we did not account for population changes in behaviour (or continued trends) that would alter population-average BMI, and we did not account for changes in population-average BMI within compartments due to differential transition rates through the disease pathway. BMI changes, and therefore rate changes, are computed only for the adult population. The epidemic model also included children and adolescents, whose disease-transition rates in all scenarios were the same as those in the Reference scenario. We did not model changes to BMI in these groups as there were no estimates available for consumption changes as a consequence of labelling specifically for their ages.[12–14] More importantly, published dose-response relationships between BMI and COVID-19 outcomes were estimated only for adults,[8] and the natures of these relationships in children and adolescents are currently not available. Any changes in COVID-19 outcomes in scenarios were therefore a consequence only of changes to infections among the adult populations.

Uncertainty

We included uncertainty in our estimates using Monte Carlo (MC) sampling with 8192 samples. We modelled uncertainty arising from population BMI values and from the dose-response relationships with COVID-19 outcomes. For the reference, no-obesity, and scenarios with historical BMI distributions, we resampled BMI values, according to the survey weights, so that each MC sample had a different distribution. For the intervention scenarios, we used published confidence intervals[13,14] to construct independent normal distributions that described the population mean change in consumption (Supplementary Tables S4 and S5), such that there was one value per subgroup in each MC sample.

We sampled dose-response relationships assuming log-normal distributions to describe relative risks, which we derived from the published confidence intervals.[8] We assumed the relative risks are independent across disease-state transitions but perfectly correlated across BMI values and age groups (e.g., a high value for the relative risk of diagnosis among one age group with a BMI of, say, 30 kg/m^2 means that the relative risk of diagnosis is also high for other age groups and other BMIs, but has no implications for values of the relative risk of hospitalisation given diagnosis).

We report the expected relative values (percentages) of outcomes with 95% prediction intervals (PI). We assessed the sensitivity of the results to the uncertain parameters using value-of-information methods (Supplementary Appendix D): we computed the expected value of partial perfect information, which is a measure of how much uncertainty in our estimated quantities would reduce if we knew a parameter or group of parameters perfectly.[24]

Ethical approval

The present study used secondary data publicly available. Hence, ethical approval was not needed.

Role of funding source

The funders of the study had no role in the study design, data collection, data analysis, data interpretation, or writing of the report. All authors had full access to the data. The corresponding author had the final responsibility for the decision to submit for publication.

Results

In all scenarios, infections, hospitalisations, YLLs, and deaths were reduced for all age groups relative to the reference scenario from January 2020 to October 2021 (percent reductions shown in Table 1, and absolute reductions shown in Supplementary Table S8). The reduction of infections ranged from 2.0% (95% PI 1.1, 2.8%) to 14.4% (95% PI 13.1, 15.7%), the hospitals days, from 3.3% (95% PI 2.1, 4.5%) to 26.9% (95% PI 24.5, 29.3%) and the YLLs from 4.6% (95% PI 2.8, 6.5%) to 44.8% (95% PI 36.8, 52.6%).

The no-obesity scenario had the largest effect on infections, hospital days, and YLL. Among the scenarios with historical BMI distributions, the largest reduction was observed in the scenario with the BMI distribution of the year 2000, with a 9.2% (95% PI 8.1, 10.2%) reduction in infections, a 15.8% (95% PI 14.2, 17.4%) reduction in hospital days, and a 23.3% (95% PI 19.2, 27.7%) reduction in YLLs. Among the intervention scenarios, the largest reduction was in the quadruple tax scenario with a 6.1% (95% PI 3.6, 8.4%) reduction in infections, a 9.7% (95% PI 6.3, 13.0%) reduction in hospital days, and a 13.3% (95% PI 8.2, 18.3%) reduction in YLLs (Table 1).

The largest relative reduction in deaths was in the no-obesity scenario (39.3%, 95% PI 32.1, 46.5%). The highest reduction among the scenarios with historical BMI distributions was that for the year 2000 (20.6%, 95% PI 16.9, 24.6%), and for the intervention scenarios, in the quadruple tax (11.6%, 95% PI 7.3, 15.8%). The labelling scenario and the scenario with BMI distribution taken from the year 2012 had a similar effect, while doubling the tax scenario had the lowest effect overall (Fig. 3).

We observed an effect on the reduction of deaths in children and adolescents (0–19 years), even though in all scenarios their BMI distribution did not change. Had the adults 20 and over had the BMI distribution of the year 2000, 14.2% (95% PI 12.4, 16.0%) and 15.6% (95% PI 13.8, 17.4%) of the deaths could have been averted in age group 0–4 and 5–19 years, respectively; and in the quadruple tax, 9.2% (95% PI 5.3, 13.0%) and 10.3% (95% PI 6.0, 14.4) (Table 2).

Scenario	Infections	Hospital days	YLL
	% (95% PI)	% (95% PI)	% (95% PI)
No obesity	14.4 (13.1, 15.7)	26.9 (24.5, 29.3)	44.8 (36.8, 52.6)
2000	9.2 (8.1, 10.2)	15.8 (14.2, 17.4)	23.3 (19.2, 27.7)
2006	4.3 (3.4, 5.2)	7.5 (6.2, 8.8)	11.5 (8.6, 15.0)
2012	2.2 (1.5, 3.1)	4.0 (2.7, 5.3)	7.1 (4.5, 10.1)
Labelling	2.9 (2.7, 3.1)	4.9 (4.5, 5.3)	7.1 (6.0, 8.2)
Double tax	2.0 (1.1, 2.8)	3.3 (2.1, 4.5)	4.6 (2.8, 6.5)
Treble tax	4.1 (2.4, 5.7)	6.6 (4.2, 8.9)	9.1 (5.5, 12.7)
Quadruple tax	6.1 (3.6, 8.4)	9.7 (6.3, 13.0)	13.3 (8.2, 18.3)

YLL: years of life lost. PI: prediction interval.

Table 1: **Relative reduction in infections, hospital days, and YLLs from the reference scenario associated with lower population BMI levels for all scenarios up to October 2021.**

The no-obesity scenario allowed us to estimate the transmission-model PAF for COVID-19 outcomes due to obesity: the reduction in expected deaths is 39.3% (95% PI 32.1, 46.5%) overall, 52.5% (95% PI 43.2, 61.6%) for adults aged 20–64 and 23.8% (95% PI 18.7, 29.1%) for adults aged 65 and over. In comparison, PAFs computed without considering transmission dynamics are 44.5% for adults aged 20–64 and 18.2% for adults aged 65 and over (Supplementary Appendix B).

In our sensitivity analysis (presented in Supplementary Appendix D), we find that, across all

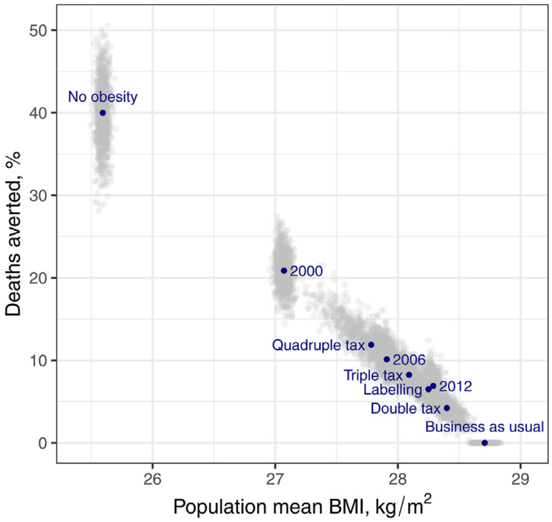

Fig. 3: **Population mean BMI among adults in all scenarios considered plotted against the percentage of deaths that would have been averted in the COVID-19 pandemic up to October 2021.** Grey dots show the 8192 Monte Carlo samples. Navy dots show mean values for scenarios.

Scenario	Age group				
	Total	0–4 years	5–19 years	20–64 years	65 and over
	% (95% PI)	% (95% PI)	% (95% PI)	% (95% PI)	% (95% PI)
No obesity	39.3 (32.1, 46.5)	23.4 (21.2, 25.5)	24.8 (22.7, 26.8)	52.5 (43.2, 61.6)	23.8 (18.7, 29.1)
2000	20.6 (16.9, 24.6)	14.2 (12.4, 16.0)	15.6 (13.8, 17.4)	27.0 (22.3, 32.3)	12.9 (10.0, 16.2)
2006	9.9 (7.3, 12.9)	6.2 (4.9, 7.6)	7.1 (5.7, 8.6)	13.8 (10.2, 18.1)	5.3 (2.7, 8.2)
2012	6.9 (4.5, 9.5)	3.2 (2.1, 4.4)	3.7 (2.4, 5.0)	7.9 (4.3, 11.2)	6.0 (3.9, 8.5)
Labelling	6.2 (5.2, 7.3)	4.1 (3.8, 4.4)	4.7 (4.4, 5.1)	8.2 (7.0, 9.4)	3.9 (3.1, 4.7)
Double tax	4.1 (2.5, 5.7)	2.8 (1.6, 4.0)	3.2 (1.8, 4.6)	5.5 (3.2, 7.8)	2.4 (1.3, 3.5)
Treble tax	7.9 (4.9, 11.0)	5.6 (3.4, 8.4)	6.7 (3.9, 9.5)	10.7 (6.4, 15.1)	4.6 (2.6, 6.8)
Quadruple tax	11.6 (7.3, 15.8)	9.2 (5.3, 13.0)	10.3 (6.0, 14.4)	15.6 (9.5, 21.8)	6.8 (3.8, 9.9)

Values for the four age groups are shown separately. The column “Total” is the weighted sum of the four age-group columns. PI: prediction interval.

Table 2: **Relative reduction in deaths from the reference scenario for all scenarios up to October 2021.**

scenarios, our estimates are sensitive to uncertainty in the relationship between BMI and the relative risk of death given hospitalisation. Within the tax scenarios, there is sensitivity also to the relationship between taxation and consumption, particularly for the age group 40–59 years old. These are the parameters that would be most beneficial to learn to increase estimate precision.

Discussion

Using simulation modelling, we show how the prevalence of obesity played an important role in the lethality and severity of the COVID-19 pandemic in Mexico. The results from the historical BMI-distribution scenarios suggest that the BMI increase of the Mexican population over the last two decades led to a population more susceptible to infection and severe COVID-19 outcomes. It is important to note that in constructing these scenarios we used only the BMI distribution: we do not capture any other ways in which population health might have changed over time, ways that might also have impacted COVID-19 dynamics for better or worse. In the historical BMI distribution scenarios, the largest reduction was in the scenario with the BMI distribution taken from the year 2000 for all outcomes—infection, hospital days, YLL, and deaths. We estimate that had the BMI distribution been as it was in 2000, COVID-19 deaths could have been reduced by 20.6% (95% PI 16.9, 24.6%) for the whole population, or 27.0% (95% PI 22.3, 32.3%) for adults aged 20–64 and 12.9% (95% PI 10.0, 16.2%) for those aged 65 and older. Among the intervention scenarios, the largest reduction was observed in the quadruple tax scenario.

The cause of the rise in obesity combines complex social and economic factors which will not be reversed by a single public health intervention.[25–27] However, our results suggest that strengthening our current interventions, such as doubling the tax for non-essential energy-dense food and SSB, could have averted between 2.5% and 5.7% of the deaths due to COVID-19. Trebling tax or implementing front-of-pack warning labels could have led to larger gains. Population-level interventions to reduce BMI are being proposed and tested across the world and they could be beneficial beyond their immediate targets, such as the reduction of obesity or chronic diseases,[14,28] extending to reducing the impact of infectious diseases such as COVID-19.

We estimated that the PAF for COVID-19 deaths due to obesity was 39.3% (95% PI 32.1, 46.5%) for the whole population, or 52.5% (95% PI 43.2, 61.6%) for adults aged 20–64 and 23.8% (95% PI 18.7, 29.1%) for those aged 65 and older. However, in the elderly groups, the BMI is more likely to misclassify individuals[29] due to physiological changes associated with ageing, so we could be under or over-estimating the PAF in this group. Our estimated PAF for deaths is greater than estimates of 30% for the US[30] and 30% for the UK.[31] The countries have similar levels of obesity, but the PAF computation did not account for disease transmission. It is also greater than the 12.8% estimated for Mexico.[11] However, the dataset used (COVID-19 surveillance) suffered from underreporting of obesity: it reported an overall prevalence of 15.2%, compared to 36.1% in ENSANUT (Supplementary Table S2).

Our results show that timely interventions to improve the underlying health state of populations pose an important opportunity for pandemic preparedness, independently of the benefits provided by the health-system response. Chronic conditions, such as obesity, hypertension, and diabetes, increase the risk of more severe forms of different infectious diseases, such as influenza H1N1.[32,33] Under a sanitary emergency, a healthier population will be a more resilient population. This not only implies lower numbers of cases, severe cases, and deaths but also a more manageable scenario for the health system to respond to, which is particularly critical for low- and middle-income countries. An example that highlights the encompassing benefits of a healthier population is our result that the number of hospital person–days required was 26.9% lower in the no-obesity scenario, which represents a substantially lower health-system burden. This would be in addition to the reductions in health-system demand due to reductions in obesity and its sequelae. While the difference in the number of infections was small relative to the differences in hospitalisations, and deaths, the difference in cases of long COVID would likely be greater, with people with obesity having an estimated odds ratio of 0.34–0.74 for recovery within one year of infection.[34]

The complexity of the dynamics between chronic diseases and the COVID-19 pandemic remains a challenge. We now have evidence that a high BMI increases the risk of COVID-19 infection in addition to severe outcomes[8]; therefore, reducing the prevalence of high BMI is also expected to reduce infection rates for all people, no matter their BMI. This insight cannot be captured by static analyses of the burden of disease such as the PAF as it is conventionally defined.[17] With a dynamic model including BMI-dependent disease transmission, we capture this effect. This is clearest in our results for COVID-19 infections and deaths in people under 20 years old, who were not subjected to changes in BMI distribution and yet had lower incidence and mortality. These reductions are a consequence of fewer infections occurring among adults aged 20 and over.

Our study has some limitations. A source of uncertainty in our model is to parameterize the effect of taxation and labelling campaigns on calories. We have used published estimates and their uncertainty in Mexico,[14] but the basis for the predicted effect of the labelling campaign is a study in Canada. For the effect of taxation, we assume a linear relationship between the level of tax and the reduction in consumption, which extends beyond the scope of the meta-analysis.[21] We accounted for these uncertainties by assigning them distributions and estimating the expected health benefits under uncertainty and assessing the sensitivity of our conclusions to these values. In encoding the epidemic model, we assumed all variables other than disease-state transition rates impacted by BMI stay the same, most notably population behaviour and government mandates. In reality, had the prevalence been lower, individuals may have reduced self-protective behaviour, and the government may have employed lighter pandemic mitigation interventions, which would have led to higher contact rates, and therefore higher infection rates. Thus, our results present an upper bound to the health gains corresponding to each scenario, and scenarios with the highest reduction in BMI, such as the no-obesity scenario, likely most overestimate transmission reduction. We assumed that the effects of vaccines are independent of BMI. There is some evidence suggesting that vaccines could be less effective at higher BMI[35]; therefore, our estimates of the impact of BMI are conservative in this respect. We also do not take into consideration how BMI impacts mortality through any means other than COVID-19; in particular, we do not account for how the population's age distribution might be different because of different BMI profiles, i.e., we do not account for the non-COVID benefits of BMI-reducing policies. Rather, we assume the same age distribution as in the reference scenario for all scenarios. Finally, we note that our method does not permit reporting of final outcomes disaggregated by ethnicity, gender, or socio-economic status. This is a limitation of our compartmental epidemic model: to disaggregate outcomes would require disaggregation of all contact rates between the groups already present in the model to account for mixing between different groups within each setting (Refer to Supplementary Appendix E5 for setting-specific contact rates estimated for our model).

Pandemic plans detail many direct actions to reduce the probability of infection, and to improve the health-system response. However, the COVID-19 pandemic provided clear evidence that the underlying health status of the population modifies the impact of an emerging infectious disease. Improving the population's underlying health should be considered as a priority pandemic preparedness strategy. Our study explored the potential impact of structural interventions in improving population health through the reduction of obesity and overweight and highlighted the magnitude of the impact that interventions might have if they were able to change the distribution of population BMI as dramatically as it has changed in the last 20 years. Similar interventions could be introduced to reduce other chronic conditions that increase the susceptibility of populations, such as undernutrition, diabetes, and hypertension. Including specific interventions to improve population health should be an integral part of any pandemic preparedness plan, particularly for countries that are currently experiencing a very large toll of chronic diseases.

Contributors
RJ took the lead on conceptualisation, formal analysis, investigation, methodology, software, validation, visualisation and writing–original draft, and contributed to data curation. MC contributed to conceptualisation, data curation, formal analysis, investigation, validation, visualisation, and writing–review & editing. ABA contributed to writing–review & editing. DH contributed to conceptualisation, software, validation, and writing–review & editing. CM contributed to conceptualisation, methodology, validation, and writing–review & editing. PD contributed to conceptualisation, software, validation, and writing–review & editing. GF contributed to conceptualisation, validation, and writing–review & editing. KDH lead on funding acquisition, project administration, resources, supervision, and contributed to conceptualisation, methodology, validation, and writing–review & editing. TBG contributed to funding acquisition, project administration, resources, supervision, and contributed to conceptualisation, and writing–review & editing. RJ, MC, CM, DH, and PD accessed and verified the data, and RJ and MC were responsible for the decision to submit the manuscript.

Data sharing statement
All data used are publicly available and cited within the text. Available hyperlinks are given in References.

Declaration of interests
KDH declares receipt of personal fees from WHO, Pfizer and GSK for work unrelated to this study, Payments for expert testimony by Infected Blood Inquiry (UK) and stocks from Astra Zeneca. GF declares receipt

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.lana.2024.100682.

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