Calculating potential impact fractions to assess the impact of tobacco control policies

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Measures of population impact

To assess the proportion of disease incidence attributable to the prevalence of exposure in a population, we can calculate the population attributable fraction (PAF)

$$\mathrm{PAF} = \frac{p(RR - 1)}{p(RR - 1) + 1}$$

Where p is the prevalence of the risk factor and RR is the relative risk of incidence of the disease of the exposed over the non-exposed

This fraction gives the proportion of incident cases observed in the population which is attributable to risk factor exposure (i.e. potentially preventable)

Measures of population impact

Example:

$$\mathrm{PAF} = \frac{\mathrm{p}(\mathrm{RR} - 1)}{\mathrm{p}(\mathrm{RR} - 1) + 1}$$

Where p is the prevalence of the risk factor and RR is the relative risk of incidence of the disease of the exposed over the non-exposed

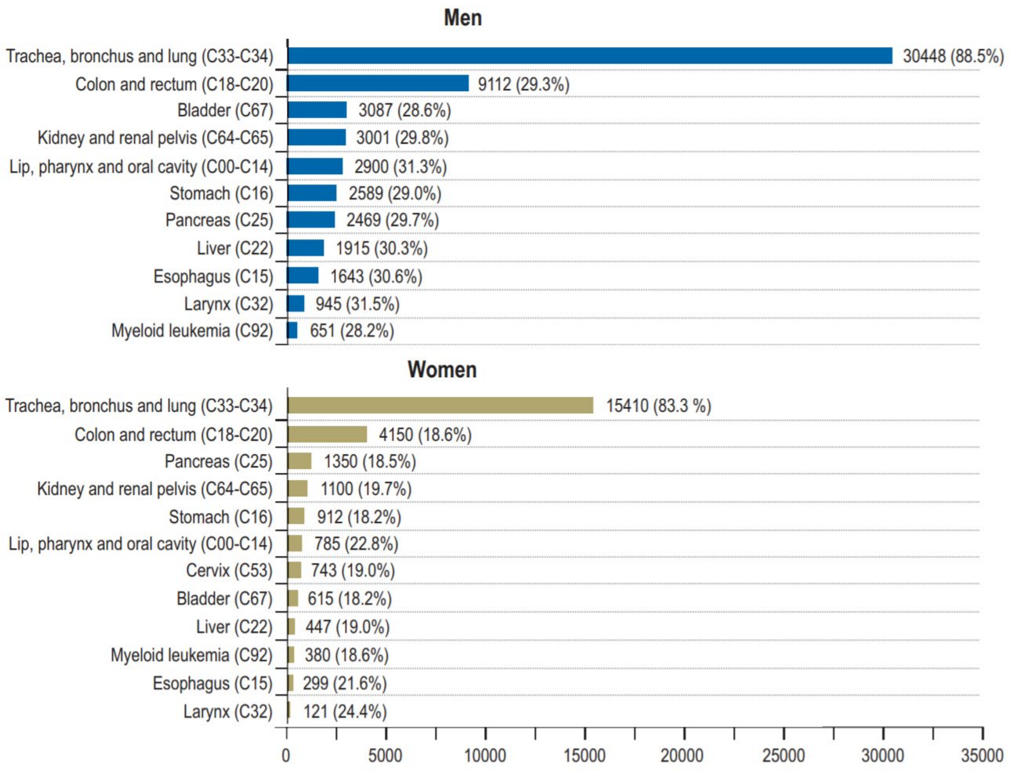
Smoking prevalence: 30%

RR for lung cancer risk in smokers: 20.0

PAF = [0.3 x (20 – 1)] / [0.3 x (20 – 1) + 1] = 0.85

➔ 85% of lung cancer cases are attributable to smoking

Cancer cases attributable to smoking (Germany 2018)



Mons et al. 2018, Deutsches Ärzteblatt International 115: 571-577

Measures of population impact

Limitations

- The counterfactual scenario might be unrealistic – attributable fractions not necessarily fully avoidable through prevention
- Static approach: long-term trends in risk factor prevalence and disease incidence, population dynamics and demographic trends, as well as lag and latency effects not considered

➔ Dynamic macro-level simulation modelling based on the potential impact fraction more adequate

Measures of population impact

Potential impact fraction (PIF)

Proportional change in disease incidence when exposure to a risk factor is changed (i.e., increased or reduced)

$$\mathrm{PIF} = \frac{(\mathrm{p} - \mathrm{p}')(\mathrm{RR} - 1)}{\mathrm{p}(\mathrm{RR} - 1) + 1}$$

Where p is the prevalence of the risk factor and p′ the counterfactual, RR is the relative risk of the exposed compared to the reference level of exposure

Measures of population impact

Example:

$$\mathrm{PIF} = \frac{(p - p')(RR - 1)}{p(RR - 1) + 1}$$

Where p is the prevalence of the risk factor and p′ the counterfactual, RR is the relative risk of the exposed compared to the reference level of exposure

Smoking prevalence = 30%

RR for lung cancer risk in smokers: 20.0

Counterfactual smoking prevalence: 20%

PIF = [(0.3 – 0.2) x (20 – 1)] / [0.3 x (20 – 1) + 1] = 0.28

➔ 28% of lung cancer cases could be avoided by reducing smoking prevalence from 30% to 20%

Application in policy intervention scenarios

Approach

Estimation of numbers and proportions of potentially avoidable disease cases under different policy intervention scenarios

1. Developing policy intervention scenarios and corresponding assumptions regarding their impact on risk factor distributions (incl. lag/latency effects)

2. Calculating the number of disease cases in the policy intervention scenarios by applying the PIF to the corresponding number of predicted cases, according to assumed impact of the intervention on the risk factor

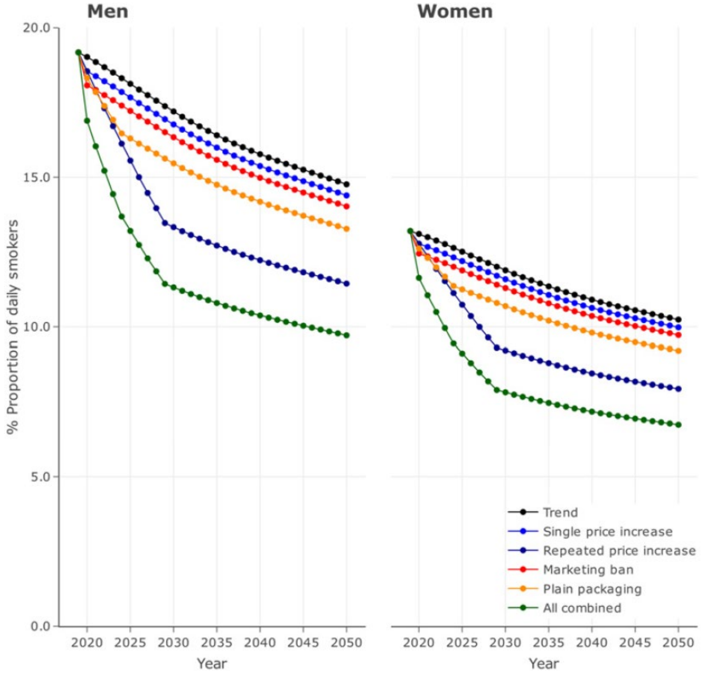
3. With the scenario reflecting the potential impact of the intervention, the difference in incidence between the intervention scenario and the reference scenario can be attributed to the intervention

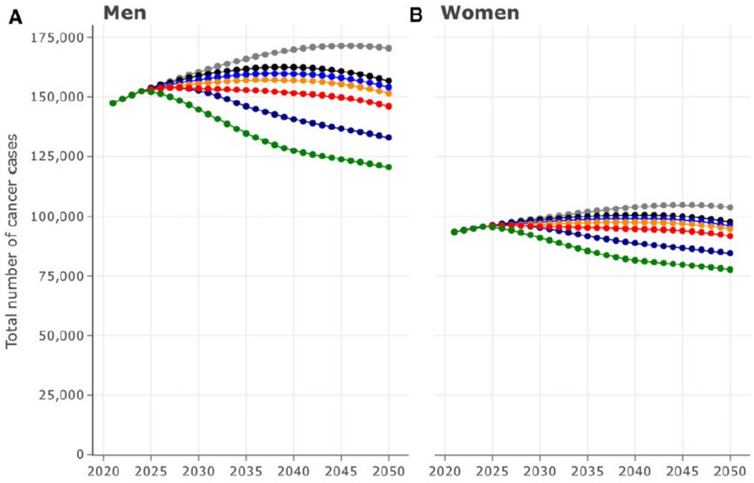
Application in policy intervention scenarios

Data requirements

- Data on risk factor distributions
- Relative risks for the risk factor-disease association
- Incidence/mortality data
- Data or assumptions on impact of policy interventions on risk factor distributions
- (Projections of future disease incidence)

Example: Impact of tobacco control policies on smoking-related cancer incidence in Germany 2020 to 2050





Gredner et al. 2020, Cancer Epidemiology, Biomarkers & Prevention 29: 1413-1422

Discussion

- Extensive sensitivity analyses are warranted to check the impact of potential biases in the underlying data and alternative model assumptions on results
- Uncertainty increases with increasing modelling durations, as incidence rates and autonomous risk factor trends might change due to other factors
- Absolute case numbers provide tangible measures of public health impact, but must be interpreted and used with caution given the uncertainties involved in estimation
- Nevertheless, when used with caution, the modelling approach provides a useful instrument to quantify the potential public health impact of interventions

Thank you for listening!

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