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Public Health Impact of Changes in Smoking Behavior

Results From the Tobacco Policy Model

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Objectives. The relative magnitude of the public health gains from preventing smoking initiation versus encouraging cessation or avoiding relapse in different ages and genders is estimated and compared.

Methods. Health gains are defined as the predicted increase in Quality-Adjusted Life-Years (QALYs) to the US population during a century. To estimate QALYs, we developed the Tobacco Policy Model. The model simulates a 10% reduction in the annual probability of initiation versus a 10% increase in cessation versus a 10% reduction in relapse in males and females in six age groups: 10 to 19, 20 to 29, 30 to 39, 40 to 49, 50 to 59 and 60 to 69.

Results. Among youth and young adults, reducing initiation yields far more QALYs than encouraging cessation or averting relapse. In middle-aged adults, cessation yields the most QALYs, followed by averting relapse and reducing initiation. In the oldest age group, averting relapse yields the most QALYs followed by cessation and reducing initiation. In general, increasing cessation and reducing relapse is more beneficial in males than in females whereas reducing initiation is more beneficial in females.

Conclusions. The relative value of preventing initiation, encouraging cessation, and averting relapse differs by age and gender. Reducing initiation in youth is likely to offer the largest public health impact during the next century.

Key words: Tobacco; smoking; simulation; quality of life. (Med Care 2001;39:1131–1141)

Interventions and policies designed to reduce tobacco use differ according to the population they are intended to reach and the nature of the behavior they are designed to alter. Physician cessation advice, for example, is often directed at older smokers and is designed to encourage them to quit. Laws restricting tobacco sales to minors, however, serve primarily to prevent youth from starting to smoke. Anti-tobacco media campaigns can be targeted at people of any age or gender and can convey any message: don't start, quit now, or don't relapse. Because these interventions affect different behaviors in different populations, their ultimate impact on the nation's health will vary.

There have been a host of studies investigating the short-term efficacy of specific tobacco use-reduction interventions and policies. However, in the quest to design a good tobacco control strategy for the nation, it seems helpful to take a step back from the specifics of policy alternatives to consider more fundamentally the long-term cumulative impact of different forms of behavior change in various populations. By starting with a broad understanding, policy analysts will be better able to target interventions in a manner that offers the greatest potential for influencing the nation's health.

Other researchers have modeled the prevalence, mortality, and economic burden of tobacco

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use[1,2] or the costs and benefits of specific interventions.[3,4,5] The present research improves on these historical approaches. We use a new simulation model, called the Tobacco Policy Model, which includes several innovations: first, we model changes in smoking behavior rather than prevalence alone. This allows us to simulate dynamic changes in behavior over time, assess health status more accurately, and contrast the relative value of preventing initiation, encouraging cessation, or averting relapse. Second, we capture not only gains in survival, but also improvements in health-related quality of life. Models that count only deaths, or even years of life lost, underestimate the larger impact of tobacco use. Third, we simulate the effects of tobacco use reduction over multiple generations. This allows us to model intergenerational influences, such as the impact of smoking during pregnancy on infant mortality. Other models estimate results for a fixed cohort over a more limited time horizon. Fourth, we recognize that not all the mortality and morbidity differential between smokers and nonsmokers is due to smoking. Most historical models attribute the entire differential to smoking, ignoring the fact that smokers often have other lifestyle factors that contribute to mortality.

In this paper we take the novel approach of abstracting away from the myriad of policy options available to ask more fundamental questions about the impact of changing tobacco use patterns in various groups. Our goal is to offer insight into the types of policies that are likely to make the biggest difference in reducing the premature death and suffering caused by tobacco use. The objective of this paper is to compare the public health gains from preventing initiation, encouraging cessation, or avoiding relapse in different genders and at different ages.

Materials and Methods

To estimate public health gains from reducing tobacco use, we developed a computer simulation model called the Tobacco Policy Model. Below we describe the model, the secondary data upon which the model relies, and the scenarios evaluated.

Tobacco Policy Model

The Tobacco Policy Model is a system dynamics computer simulation model constructed using Vensim 4.0 software. It is designed to calculate the gains in quality-adjusted life-years (QALYs) given changes in tobacco use. The model simulates birth, death, aging, and changes in smoking behavior in the US population. The population is divided into cohorts according to age, gender and smoking status. Transitions such as aging, birth, death, smoking initiation, cessation, and relapse are assumed to occur annually. Transition probabilities can vary by age, gender, smoking status, and year.

Model Variables and Data

We initialized the simulation model with the US population in the year 2001. To estimate the composition of the population by age and gender, we used "middle series" projections from the US Bureau of the Census.[6] We also divided the initial population according to their smoking status: current, former, or never smoker. Consistent with standard practice, we defined current smokers as those who have smoked at least 100 cigarettes in their lifetime and have smoked in the past 30 days. Former smokers are those who were once current smokers but have not smoked in the past 30 days. Never smokers are persons who have not smoked 100 cigarettes in their lifetime. To estimate the number of current, former and never smokers of each age and gender, we used the Behavioral Risk Factors Surveillance Survey[7] for adults aged 18 and older, the National School-Based Youth Risk Behavior Survey[8] for teenagers aged 14 to 17, and the Teenager Attitude and Practice Survey II (TAPS II)[9] for children aged 8 to 13. We assumed that all children under age eight are never smokers.

We simulated three types of change in smoking behavior: initiation (the transition from being a never smoker to being a current smoker), cessation (current smoker to former smoker), and relapse (former smoker to current smoker). To simulate annual behavior change, we derived transition probabilities by comparing smoking status in two consecutive years. Thus, "cessation" in our model does not necessarily imply permanent cessation—it can be, and often is, a temporary state until the former smoker relapses. Because no single survey includes all data necessary to estimate all behavior change probabilities for all age groups, we used data from several sources. To estimate the probability of initiation, we used the

Current Population Survey, Tobacco Use Supplement.[10] To estimate the probability of cessation and relapse, we used the National Health Interview Survey[11] for adults, and the TAPS II[9] for youth. Using regression methods, we fit separate hazard functions by age, gender, and interaction terms.

We obtained data on the probability of a live birth from the Census.[6] Mortality data for current, former and never smokers were taken from the 1992 National Health and Nutrition Examination Survey I, Epidemiologic Follow-up Study.[12] We assumed that infants born to mothers who smoke during pregnancy have a 58% higher infant mortality rate than those born to mothers who do not smoke during pregnancy.[13] For youth and adults, we computed mortality hazard functions for each smoking status and gender assuming a Weibull distribution. The Weibull has been widely used in tobacco-related analyses to model all-cause and disease-specific mortality.[4,5,14] We used these functions to adjust gender-specific mortality hazards[6] for the years 1995, 2005, and 2050, and then interpolated the hazard rates for intermediate years.

To quantify public health outcomes we use the Quality Adjusted Life Year (QALY) measure. The QALY is convenient because it combines improvements in length of life and health-related quality of life into a single measure. To measure the quality of life implications of health problems in adults due to smoking, we used estimates derived from the Quality of Well Being Scale (R.M. Kaplan, written communication, June 3, 1999), a widely used and respected scale for assessing health-related quality of life.[15,16] Kaplan elicited separate estimates from male and female current, former, and never smokers in various age groups starting at age 17. For example, females aged 40 to 44 who were current smokers reported an average quality of life of 0.83, former smokers 0.87, and never smokers 0.88. We supplemented these quality of life data for adults with comparable data for youth taken from Erickson et al.[17] Erickson estimated the QOL for children using health status data from the National Health Interview Survey. They calculated that the average QOL for children age 0 to 5 was 0.94 and for children age 6 to 8 it was 0.93. Using the combined data, we used polynomial regression to estimate health-related quality of life as a function of age, gender, and smoking status.

Scenarios Evaluated

We evaluated the impact of three types of behavior change (initiation, cessation, or relapse) in each gender and six age groups (10–19, 20–29, 30–39, 40–49, 50–59 or 60–69). To simulate behavior change, we used two strategies. First, we modeled a 10% change in the annual probability of initiation, cessation or relapse and retained the changed probabilities for that age range every year throughout the duration of the 100-year simulation. Second, we modeled a one-time behavior change in cohorts of fixed size. Each strategy is explained in more detail below.

When using the first strategy, we altered the probability of some smoking behavior change by 10% in a particular gender and age group. For example, we simulated the impact of reducing the annual probability of initiation by 10% in male never smokers aged 10 to 19. In a separate simulation we modeled the impact of increasing the annual probability of cessation by 10% in male current smokers in the same age category. In a similar fashion, we simulated the impact of decreasing the annual probability of relapse by 10% for male former smokers. To implement one of these scenarios, we altered the relevant probabilities for all males passing through the 10 to 19 “age window” at any point during the course of the 100-year simulation. As each person exits the “age window” (ie, turns age 20 in this case) they resume the probability of behavior change appropriate for their age and gender.

Note that in the above strategy, the magnitude of public health gains due to each type of behavior change will be influenced by the number of people affected, which varies naturally in the population. For example, among youth there are more never smokers who are starting to smoke than current smokers who are quitting; as a result, reducing initiation by 10% will affect more people than increasing cessation by 10%. So, to better understand the public health impact of each type of behavior change on a per-capita basis, we introduced a second strategy: We held constant the number of people affected assuming that a fixed number (5,000) would alter their smoking behavior for 1 year and then resume their natural probability of behavior change in subsequent years. For example, when estimating the public health gains from avoiding initiation in male youth aged 10 to 19, we assumed that 5,000 male youths who would have become current smokers in the year 2001 instead remained never smokers for that year. When modeling the impact of cessation, we assumed that an extra 5,000 male youth current smokers would quit in the year 2001. Finally, when modeling the impact of averting relapse, we assumed that 5,000 male youth former smokers, who would have relapsed in the year 2001, remained former smokers for that year. We further assumed that after the first year of the simulation, all behavior change probabilities revert to the natural probabilities that are appropriate for each age and gender. So, for example, an 18-year-old prevented from starting to smoke in 2001 might or might not begin in 2002, with the probability of initiation set at that of a typical 19-year-old male.

The two strategies allow us to answer different questions. The first is meant to capture the intent of most tobacco policies that seek to change the likelihood of a certain tobacco use behavior (eg, initiation) in perpetuity. Because the impact of these policies will, in fact, vary according to the size of the population affected, it is important to understand the estimated magnitude of these effects. The second strategy is meant to offer insight into the relative value of preventing one person from starting to smoke, getting one person to quit, or getting one person whom has quit to not relapse. The choice of cohort size is inconsequential because dividing QALYs gained by the cohort size provides an estimate of the expected gains per person affected.

To estimate the gain in QALYs for each scenario, we performed a baseline 100-year simulation run assuming that each person retains their natural probability of behavior change, and then a separate simulation assuming the behavior change (caused by some intervention) in a particular age group and gender. In each simulation, we estimated the cumulative gain in QALYs to the US population for each year during one century. Consistent with the recommendations of the Office of Disease Prevention and Health Promotion's Panel on Cost-effectiveness[18] we discounted QALYs back to 2001 at an annual rate of 3%. To estimate the expected gain in QALYs due to the behavior change we subtracted the total QALYs under the baseline scenario from total QALYs with the intervention in place.

Sensitivity Analysis

The health problems experienced by smokers are due in part to smoking and in part to other factors. For example, men who smoke are also more likely to drink, have a sedentary life-style, eat a high-fat diet, be exposed to asbestos, and even drive more dangerously than those who have never smoked.[14] Based on national estimates,[14,19,20,21] we assume that 30% of the differential in mortality between smokers and nonsmokers is attributable to the smoking behavior. We made the same assumption for the differential in health-related quality of life.

The above estimate of attributability is uncertain. Consequently, we performed a series of sensitivity analyses to better understand the impact of this assumption on our results. We reflected our uncertainty in attributability using a normal distribution with a mean of 0.3 and SD of 0.08, ranging from 0 to 0.6. The mean of this distribution was chosen to reflect our best estimate of 30%; the SD ensured a reasonable range between 0% and 60%; and the choice of the normal distribution reflected our judgment that attributability was more likely to be near 30% than at the extremes. We assumed that an estimate of attributability appropriate for mortality was also appropriate for health-related quality of life. We then performed a Monte Carlo simulation: we drew a random number between 0 and 0.6, applied the appropriate mortality and QOL attributability estimate, ran the simulation, and calculated QALYs gained due to the intervention. In the same fashion, we drew 4,999 more parameters and ran the simulation a total of 5,000 times.

Results

For each scenario, the estimated gains in QALYs after a century are summarized in Table 1. The scenario yielding the largest public health gains to the US population is preventing initiation in youth aged 10 to 19. During a century, we estimate that more than one million QALYs will result from a 10% reduction in the annual probability of initiation in males aged 10 to 19. Preventing initiation in female youth offers slightly smaller gains at approximately 999,000 QALYs.

Figure 1 shows the increase in cumulative QALYs over time and contrasts the relative value of changing initiation, cessation or relapse rates for cohorts aged 10 to 19 and 20 to 29. It is clear from Figure 1 that at all points in time, reducing initiation in youth and young adults yields far more public health gains than a change of a similar

TABLE 1. Estimated Gains in Quality-Adjusted Life-Years After a Century Given a 10% Change in Initiation, Cessation, or Relapse

	Smoking Behavior Change		
Group	10% Annual Reduction in Initiation	10% Annual Increase in Cessation	10% Annual Reduction in Relapse
Age 10–19			
Male	1,058,000	7,400	610
Female	999,000	5,800	640
Age 20–29			
Male	369,000	60,000	7,300
Female	473,000	45,000	6,000
Age 30–39			
Male	42,000	103,000	36,000
Female	49,000	58,000	20,000
Age 40–49			
Male	19,000	151,000	84,000
Female	22,000	87,000	48,000
Age 50–59			
Male	13,000	190,000	155,000
Female	17,000	125,000	95,000
Age 60–69			
Male	9,100	185,000	244,000
Female	14,000	143,000	163,000

magnitude in cessation or relapse. After 10 years, reducing the annual probability of initiation by 10% in youth yields approximately 18,000 QALYs for males and 13,000 QALYs for females; after 50 years gains are 313,000 QALYS for males and 276,000 QALYs for females; and after 100 years, gains are approximately one million QALYs for both genders. Cumulative gains from a 10% increase in cessation or a 10% reduction in relapse during youth are much smaller—under 7,500 QALYs, even after a century. For young adults aged 20 to 29, reducing initiation continues to be the intervention that yields the most health gains (369,000 and 473,000 for males and females respectively), but gains from intervention in this age group are less dramatic than gains for intervention in the 10 to 19 age group.

In Figure 2 we depict the estimated increase in QALYs for the 30 to 39 and 40 to 49 age groups. In these groups, increasing cessation offers the largest gain in QALYs at all times during the century for both genders: 103,000 for males and 58,000 QALYs for females. In addition, although offering fewer gains than cessation, preventing relapse in the 30 to 39 age group is more helpful than preventing initiation in the short term whereas

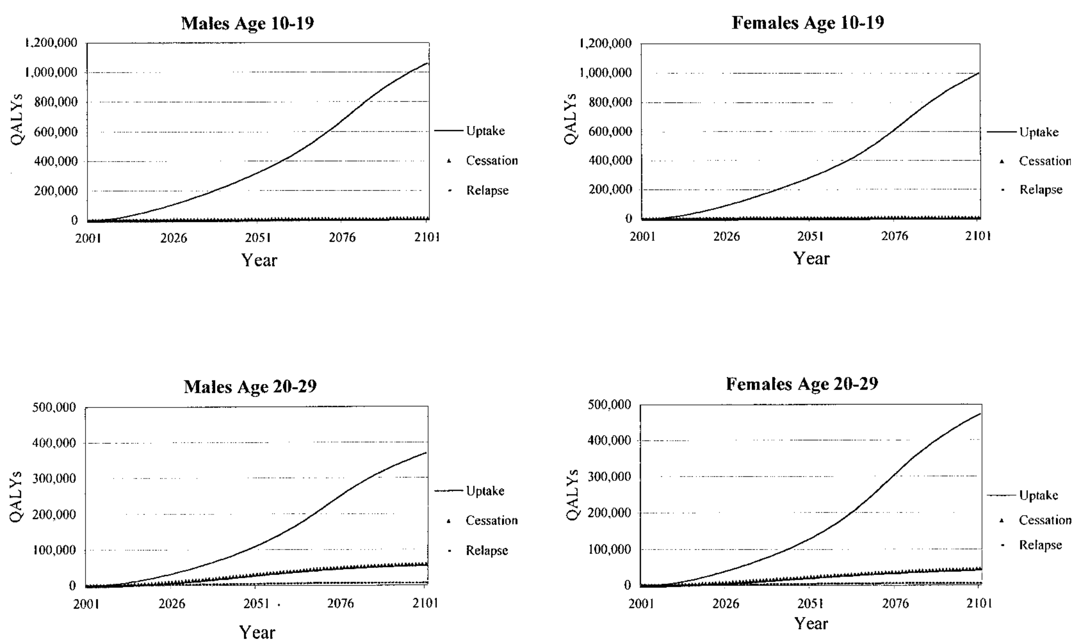

FIG. 1. Cumulative gains in quality-adjusted life-years (QALYs) given a 10% change in tobacco use behavior in age groups 10–19 and 20–29.

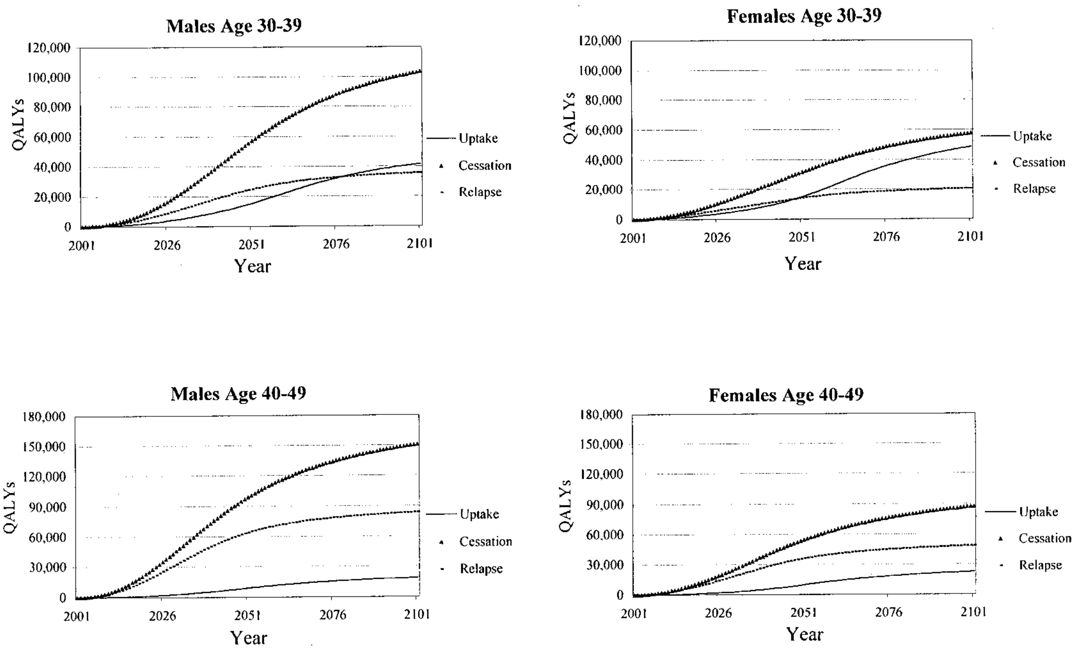

FIG. 2. Cumulative gains in quality-adjusted life-years (QALYs) given a 10% change in tobacco use behavior in age groups 30–39 and 40–49.

reducing initiation is more helpful than preventing relapse in the long term. Compared with adults aged 30 to 39, increasing cessation in those aged 40 to 49 saves more QALYs.

As shown in Figure 3, the results for older adults aged 50 to 59 continue the same ordering seen in adults aged 40 to 49. However, in the oldest age group, 60 to 69, the pattern changes again so that averting relapse will likely offer more health gains (244,000 and 163,000 for males and females, respectively) than cessation (185,000 and 143,000 for males and females, respectively). Reducing initiation offers comparatively little public health value for both genders aged 50 to 59 and 60 to 69—less than 17,000 QALYs after a century.

As shown in Table 1, as both men and women age, the value of reducing initiation declines and the value of encouraging cessation and averting relapse increases. Further, at almost all ages, changing cessation or relapse probabilities in males offers more gains than changing these same probabilities in females. The opposite is true for initiation where preventing initiation in females offers more gains than preventing initiation in males. The exception is for youth aged 10 to 19 where preventing initiation offers more gain in males than in females.

All the above results were estimated with the Tobacco Policy Model assuming a 10% annual change in smoking behavior. We also used the model to simulate health outcomes assuming a one-time behavior change in a cohort of fixed size. QALYs gained per person affected are summarized in Table 2. Per capita, reducing initiation yields more gains than changing cessation or relapse in each and every age and gender category. Further, the value of all forms of behavior change increases with age. In general, preventing females from initiating is more helpful than preventing males from initiating, whereas encouraging cessation and averting relapse in men are more helpful than in women, particularly at older ages.

We explored the sensitivity of our results to assumptions about the extent to which the mortality and quality of life differences in smokers can be attributed to their smoking behavior. Figure 4 illustrates the confidence bounds associated with results for the scenario where we increase the annual probability of cessation by 10% in women aged 40 to 49. Previously we assumed that attributability was 30%, but after performing a Monte-Carlo sensitivity analysis, varying it from 0% to 60%, it is clear that uncertainty in attributability leads to pronounced uncertainty in the gain in

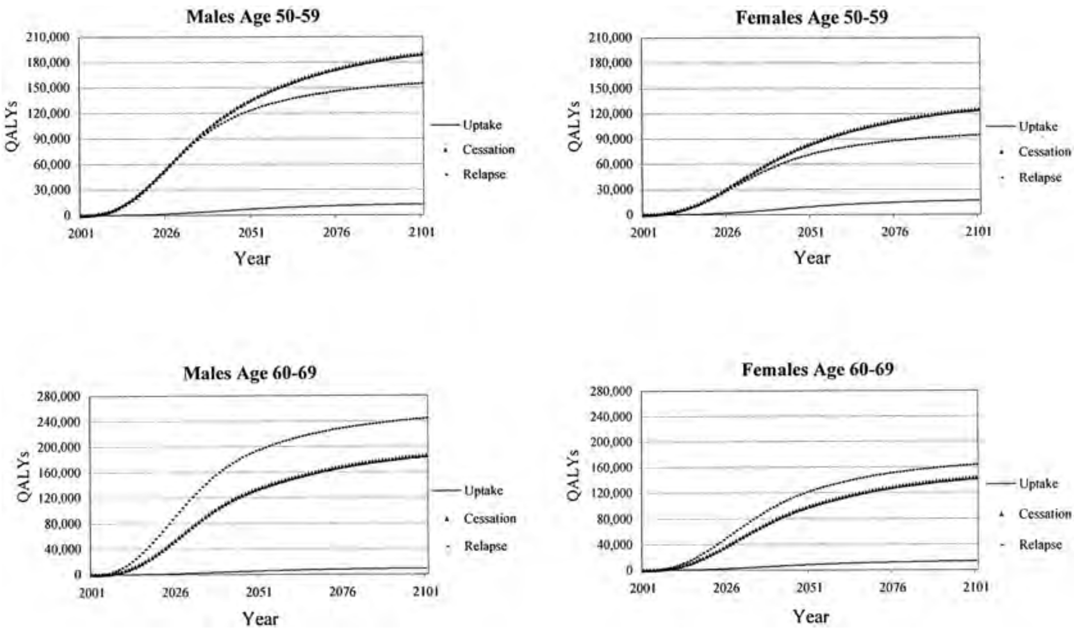

FIG. 3. Cumulative gains in quality-adjusted life-years (QALYs) given a 10% change in tobacco use behavior in age groups 50–59 and 60–69.

TABLE 2. Estimated Gains in Quality-Adjusted Life-Years After a Century Due to a One-Time Change in Smoking Behavior of a Single Person

Group	Smoking Behavior Change		
	Reduction in Initiation	Increase in Cessation	Reduction in Relapse
Age 10–19			
Male	0.57	0.17	0.18
Female	0.76	0.26	0.26
Age 20–29			
Male	0.84	0.22	0.22
Female	0.98	0.24	0.24
Age 30–39			
Male	1.14	0.32	0.33
Female	1.15	0.20	0.21
Age 40–49			
Male	1.33	0.43	0.43
Female	1.33	0.26	0.26
Age 50–59			
Male	1.43	0.49	0.49
Female	1.40	0.33	0.33
Age 60–69			
Male	1.23	0.50	0.49
Female	1.29	0.37	0.37

QALYs. Further, it is apparent from the increasing vertical width of the curve in Figure 4 that this uncertainty grows over time. With our original estimate of attributability, the gain in QALYs due to cessation in women was approximately 87,000. If, however, attributability is 0%, then no QALYs will be realized, and if attributability is 60% then the gain in QALYs could be as much as 178,000 after a century. In subsequent sensitivity analyses, we found that estimated health gains from reducing initiation were much less sensitive to our assumption of attributability than gains from changing cessation and relapse behaviors. In addition, for all types of smoking behavior change, estimated gains from intervening at younger ages were less sensitive than at older ages.

Discussion

This simulation suggests that during the next century, reducing initiation in youth is likely to offer more public health gains to the nation than any other option examined here. The estimated QALYs gained from getting adolescents to not start smoking are 6 to 7 times greater than the

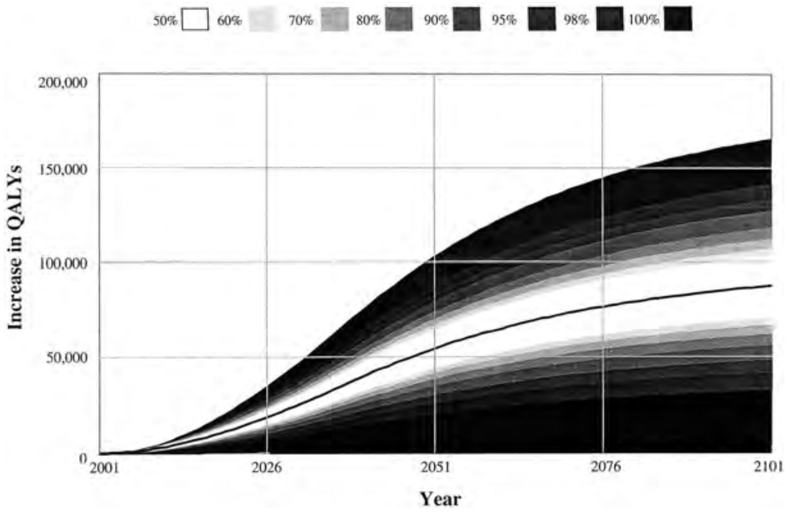

FIG. 4. Confidence in expected gain in quality-adjusted life-years (QALYs) given a 10% increase in the annual probability of cessation: Females age 40–49.

QALYs gained from getting older smokers to quit. Reducing initiation in the 20 to 29 age group also offers large health gains.

Relative to the differences by age and type of behavior change, gender differences are smaller. Any differences are due in large part to three factors. First, for results shown in Table 1, the number of persons affected differs by gender. For example, cessation and relapse are behaviors that only current and former smokers can engage in and so changing the likelihood of these behaviors in a larger group (males) yields more gains than in a smaller group (females). Second, smoking has a bigger impact on mortality rates in men than in women. So, for example, getting an older man to quit will result in a larger gain in survival than getting an older woman to quit. Third, our data indicates that smoking has a bigger impact on health-related quality of life in men than in women. One striking gender difference was observed for the scenario of reducing initiation in the 20 to 29 age group. This is the age at which many women have children. Because smoking during pregnancy increases the chance of infant mortality, and because we modeled the intergenerational influence of smoking, we observed notable population differences in QALYs gained depending on whether we change tobacco use in men or women in this age group.

The public health gains expected from preventing initiation tend to decrease with age, whereas the gains from increasing cessation and reducing relapse increase with age. Again this is due in part to the sheer numbers of persons affected. Most initiation occurs before age 18,[7,8,9,10] and so reducing the high probability of initiation by 10% results in a large impact. In contrast, few people start smoking in middle age and so altering this small probability by 10% has little impact. The opposite phenomenon occurs for cessation and relapse in part because these behaviors are more common among adults. In particular, the relative importance of relapse prevention becomes particularly pronounced with age; this reflects both the fact that relapse rates rise with age and the fact the number of former smokers increases with age.[7,11]

Over time, the confluence of probabilities has certain dynamic and synergistic effects. For example, by reducing the risk for initiation in youth, we effectively "protect" teenagers during a vulnerable window of time, and then launch them into their adult years during which they have a low probability of ever starting to smoke. Adults, because they tend to quit and relapse many times before quitting for good,[22,23] are benefited many times by a lower annual probability of relapse, or a higher annual probability of cessation. Finally, the mortality and quality of life differentials between smokers and nonsmokers increase with age. Youth tend to have a similar health status regardless of whether they smoke or not, but this is not true for older persons. Thus, getting an older smoker to quit or avoid relapse has a larger influence on their overall health status in their 60th year than it would have had in, say, their 10th year.

Comparing results during the century reveals that, regardless of the intervention, few health gains are realized in the first few decades. Large differences are apparent only after smoking behavior has been continuously modified for decades. This suggests that achieving important public health gains from reducing tobacco use requires a long-term commitment and perspective.

Results from the "one time" intervention scenario in a "fixed" population help us to understand and explain the differences previously observed in the "percent change" scenario. In particular, reducing initiation continues to yield the greatest public health gains in the "fixed" scenario and so it is clear that the observed effect in the "percentage change" scenario is not due solely to the sheer number of never smokers impacted. However, although reducing initiation previously offered gains that were on the order of 100 times greater than increasing cessation or averting relapse in the same age group, per capita gains are on the order of four times greater. Further, it is clear that on a per capita basis, encouraging cessation and preventing relapse offer almost identical health benefits. Previously their relative value differed by age, but this was due in large part to the number of persons affected: only current smokers can quit and only former smokers can relapse and so previously we saw age-related differences that were driven by the decreasing number of current smokers and increasing number of former smokers during the century.

The "one-time fixed" and "percentage change" scenario results will be useful to different decision-makers in different situations. For example, a community health program with a limited budget to fund smoking cessation classes of a fixed size might benefit from examining our per capita results. They might conclude that classes targeted to older adults, particularly men, are likely to yield the greatest health gains. In contrast, a state health department developing anti-smoking ads might rely on our percentage change results and conclude that ads targeted at reducing initiation in youth offers the greatest health gains.

In the present version of the Tobacco Policy Model we recognized that the differences in mortality and quality of life between smokers and nonsmokers are not due entirely to tobacco use. Considering attributability is important because policies designed to alter tobacco use are not generally designed to alter other patterns of behavior. Consequently, they should not take "credit" for erasing all health differential between smokers and nonsmokers. Attributability, however, is uncertain. We used the best estimate we could find, assuming that 30% of the differential is due to smoking, but in sensitivity analysis we found that the precise value will have an important impact on predicted public health gains from reducing tobacco use. This is especially true for interventions focused on older ages and those targeting cessation and relapse behaviors. Because of this large impact, additional research should be performed to determine the extent of attributability in these groups. In the meantime, our results suggest that interventions aimed at initiation and targeting the young are more robust.

There are two caveats that will aid the reader in interpreting these results. First, the magnitude of estimated health gains are a function of the percentage change in behavior that we examined. If we had chosen a larger or smaller change, we would surely have found larger or smaller outcomes. The results for each scenario are most useful for judging the relative, rather than the absolute, magnitude of the importance of any behavior change.

Second, although the Tobacco Policy Model is one of the most sophisticated tobacco-simulation models in use today, it has certain limitations. For example, it does not currently take into account the number of years smoked or the time since a former smoker quit nor does it take into account the amount of tobacco consumed (eg, packs). Further, although we divided the population according to smoking status, age, and gender, we have not yet stratified by race, socioeconomic status, or education. In addition, we use the Weibull distribution to model mortality. An alternative to the Weibull is the Gompertz distribution, which results in a steeper mortality curve at older ages. If it is indeed a better fit then the Tobacco Policy Model may be underestimating the differential in mortality between smokers and nonsmokers, thereby underestimating the QALYs gained especially from behavior change in older age groups. Further, the model does not yet incorporate all social or environmental factors. For example, as smoking rates decline youth might be less likely to initiate smoking because they want to be more like their peers, or declines in smoking might have the opposite effect, presenting the opportunity to be different and rebel. In adults, large tobacco-related mortality among one's peers can serve as a stimulus to cessation. Couplings like these have proven helpful in modeling the epidemiology of diseases, such as acquired immunodeficiency syndrome, and represent an important opportunity for further study. The hazard of environmental tobacco smoke (ETS) exposure is also not incorporated. The inclusion of ETS might serve to further increase the population-wide value of reducing tobacco use in women, as they are the major source of exposure for children. Further, although we take the unprecedented step of modeling "attributability," the absence of more refined data caused us to use the same estimate for both mortality and quality of life over all ages, genders, and types of smoking behavior change. When future scientific studies provide improved estimates specific to each group, it will be possible to include them in the Tobacco Policy Model. Finally, as with all simulation models, the results presented here are only as good as the data and modeling assumptions upon which they are based. If the data are flawed or if any of the aforementioned limitations are of critical importance, then our results will be off. Short-term results are probably more robust than long-term results but all results should be treated as estimates.

Combined with other information, these results should prove useful in informing national tobacco control policy. For example, we can say that it is probably better to prevent initiation in youth than encourage cessation in adults, *all other things being equal*. However, all other things are not generally equal. Our results should not be construed to imply that interventions affecting populations other than youth, or affecting behaviors other than initiation, are not good practice as well. To judge the economic efficiency of an intervention or policy, anticipated population health gains must be combined with other information such the effectiveness of the intervention, the economic resources consumed by the intervention, and any medical cost savings due to avoided tobacco-caused disease.[18] It could well be that a policy or intervention that yields few QALYs might still be cost-effective and thus warrant adoption. For example, at less than $5000 per QALY gained, the AHCPR guideline for smoking cessation has been shown to be cost-effective in adults.[5]

In conclusion, our simulation suggests that the tobacco use reduction strategy that will have the greatest—and perhaps most certain—impact on the health of the US population during the next century is reducing initiation in youth and young adults. Programs focusing on cessation and relapse are likely to yield substantial gains only when directed at older adults. Interventions focusing on men are likely to have more impact than those focusing on women when directed at cessation and relapse in older persons. During prime childbearing years, however, discouraging women from smoking will also reduce infant mortality and thus have a more profound influence on population health.

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