CHEST

Original Research

ENVIRONMENTAL HEALTH

How Frequently Should Workplace Spirometry Screening Be Performed?

Optimization Via Analytic Models

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Background: **Our objective was to determine how to select the optimal frequency of workplace spirometry screening using diacetyl-exposed workers as an example.**
Methods: **A Markov model was constructed to assess the likelihood of progressing from healthy status to early or advanced disease, starting from four different exposure levels, and performing longitudinal or cross-sectional interpretation of spirometry results over time. Projected outcomes at 10 years were evaluated to inform the optimal frequency of workplace spirometry testing.**
Results: **The optimal screening interval depends on the population risk and is highly sensitive to the real-life impact (utility) associated with false-positive results (*eg*, related to the availability of alternative work). Screening interval is particularly important for high-risk individuals with rapid transition from early to advanced disease, where the 10-year prevalence of advanced disease would be reduced from 5.3 to 2.5% using a 6-month interval rather than a 12-month interval. Longitudinal test interpretation, based on observing trends within each person over time, is marginally preferable to traditional cross-sectional spirometry interpretation.**
Conclusions: **There is no single best screening interval. For high-risk populations, annual testing may be too infrequent.** ***(CHEST 2009; 136:1086–1094)***

Abbreviations: DiBO = diacetyl-induced bronchiolitis obliterans; OSHA = Occupational Safety and Health Administration

Spirometry screening in the occupational setting is a well-established practice and has been mandated in numerous Occupational Safety and Health Administration (OSHA) standards.[1–5] Spirometry screening is usually offered at annual or less frequent intervals. The results of each test are compared to the distribution of results from a healthy population.[6] There is a need to consider the application of alternative paradigms such as interpretation of trend rather than cross-sectional results and other screening frequencies.

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Optimizing spirometric screening program for a worker population or for an individual worker requires the consideration of multiple factors, and the optimal approaches may not be self-evident. There is often a tradeoff between the benefits of a highly sensitive approach to detect all possible cases vs having greater specificity to avoid incorrectly mislabeling many individuals as "abnormal." This article describes a decision-analytic approach to answering the question, "How frequently should spirometry be performed?" The analysis is applied to the problem of diacetyl-induced bronchiolitis obliterans (DiBO), which underscores the limitations of the traditional approach. Disabling irreversible airflow obstruction can develop over a relatively short time in workers exposed to this flavoring product, yet removal of the worker from exposure can effectively prevent severe disability.[7–10] Regulatory approaches (*eg*, OSHA) often specify screening frequency for specific exposures to chemical agents.

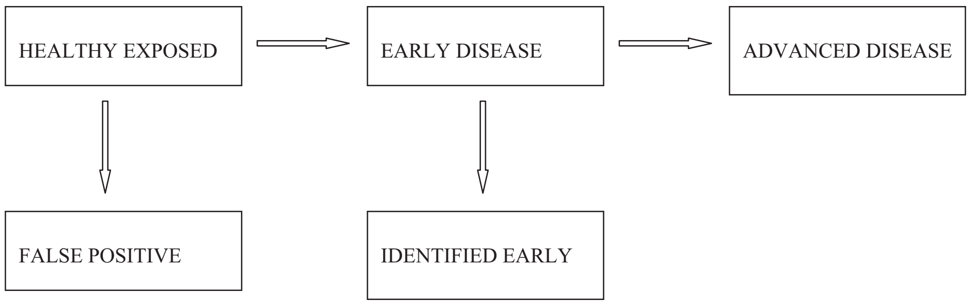

FIGURE 1. Decision-analysis model.

Materials and Methods

Using DiBO as a model, a decision-analysis Markov model (Fig 1) was developed to assess factors quantitatively that should inform program development. Table 1 summarizes the steps of model development. Individuals are classified into the following several discrete categories according to health status and screening outcome, as shown in Figure 1:

- Healthy exposed;
- Early disease: early fixed obstructive abnormality;
- Advanced disease: severe DiBO with permanent disability;
- Identified early: identified during the early stage; and
- False-positive result: a person without DiBO who is incorrectly labeled as diseased.

Table 1—*Steps in Model Development and Utilization*

Steps	Tables	Figures
Define model		1
What are the possible health categories?		
Estimate parameters for natural course of disease	2	
How frequently and quickly do individuals progress among the health categories?		
Calculate population distribution over time (natural course)		2, 3
How quickly and frequently does disease develop? How long do individuals remain in the early disease state (disease present but no symptoms)?		
Impact of screening		2, 3
How well does screening change the natural course?		
Screening intervals		2, 3
What is the effect of screening at frequencies other than annually?		
Assign utilities to outcome states	3, 4	
How beneficial or adverse are each of the health status conditions?		
Test performance	5	
How do the inherent and operational characteristics of the spirometry screening test affect long-term outcomes?		
Interpretation strategy: cross-sectional or longitudinal	3, 4, 5	4
Is evaluation of each worker's slope over time better than traditional comparison of each result to normal populations?		
Synthesis		
What is the best screening strategy for a particular population or individual?		

The Tables and Figures columns indicate where the relevant results are shown.

Individuals may progress from the healthy exposed to the early stage and from early to advanced disease. Because early disease is not associated with apparent symptoms, early cases are detected only by screening programs. Conversely, individuals with advanced disease are likely to see physicians for significant symptoms. Identified cases derive from persons in the early disease state, and false-positive cases from those in the healthy exposed category.

The model was defined by several groups of parameters. These groups describe the natural course of the disease, reflect the characteristics of the screening test, and represent programmatic decisions. Two parameters reflect the natural history of the disease:

- Transition probability from healthy to early disease: this is the monthly probability that a healthy person will progress to early disease; and
- Transition probability from early to advanced disease: monthly probability of an individual in the early disease category advancing to advanced disease.

Model Operation

Calculations were performed using commercially available decision support software (TreeAge ProSuite 2007, release 1.2; TreeAge Software Inc; Williamstown, MA), and graphical displays were developed using a spreadsheet program (Excel; Microsoft Corp; Redmond, WA). Sets of parameters were provided to the calculation engine, which then calculated the distribution of subjects monthly in each of the five states. All were in the healthy-exposed category in the first month. The number of individuals changing states in any month is calculated as the transition probability multiplied by the number of individuals in the state at the beginning of the month. The number of workers in the states at the end of the month is determined by the number at the beginning of the month minus those who transition out of the state plus those who transition into the state. For simplicity, identified, false-positive, and advanced disease are considered absorbing states, such that individuals do not leave the state once they enter it. The calculations describe the distribution in each state on a monthly basis over 10 years. For calculation purposes, the FEV_1 was employed as the single most relevant spirometry parameter, but other parameters such as the FEV_1/FVC ratio might also be employed.

Table 2—*Selection of Parameters Describing Natural Course*

Degree of Risk	TH→E	TE→A	10-yr Outcome P(Early)	P(Advanced)
Low risk	0.25%	20%	1%	1%
	0.50%	20%	2%	3%
	1.00%	10%	6%	3%
Moderate risk	1.00%	20%	4%	5%
	2.00%	10%	10%	6%
High risk	4.00%	20%	13%	20%
High risk with	4.00%	40%	7%	26%
rapid progression	8.00%	10%	32%	22%

The possible effects of risk levels (encoded as transition probabilities) upon the proportion of individuals with early and advanced disease at 10 years. The low, moderate, high, and high-rapid progression risk models were used for subsequent calculations. TH→E = monthly probability of transition from healthy to early disease; TE→A = monthly probability of transition from early disease to advanced disease; P(Early) = proportion of persons with early disease; P(Advanced) = proportion of persons with advanced disease.

Results

Defining Parameters

The published literature was surveyed to identify studies that may provide estimates for the parameters. Although few studies have followed workers sufficiently long enough to fully describe the parameters such as transition probabilities, the cross-sectional studies and case series suggest reasonable ranges. The prevalence of advanced disease even in high-risk workplaces has generally been ≤ 20%. Additionally, case reports have shown that progression from early airflow obstruction to advanced disease can occur within 1 to 2 years.[7–19] Therefore, any combination parameters that exclude these ranges were discarded.

Basic Model Results

In the initial step, the proportion of workers in each of the five possible states for each month is estimated with various combinations of possible transition probabilities. Table 2 shows several sets that yield results that are compatible with the limited empirical data. Four sets of parameter values are shown; three represent low-risk, moderate-risk, and high-risk situations. The "high-rapid" set includes more rapid progression from early to advanced disease; the total proportion of workers affected is the same for both high-risk and high-rapid situations. Several other combinations were rejected because of inconsistency with empirical data. Figure 2*A* shows the number of high-risk workers in early and advanced disease categories for each month over the 10-year span in the absence of screening.

Test Performance Characteristics

The effectiveness of screening depends on the sensitivity and specificity characteristics of the screening test. However, analysis suggested that the traditional clinical approach of selecting criteria to fix the false-positive fraction at 5% will lead to the accumulation of a large number of false-positive results when the test is performed repetitively for each person (*eg*, 40% with annual screening and 64% with semiannual screening). Because this is unrealistic, the model was extended to delineate the following two distinct causes of false-positive test results: test variability (noise) occurs with each measurement, representing the likelihood that a healthy individual will be falsely identified as abnormal because of test variability; and population variability, indicating that some individuals have inherently smaller lungs than the population average, is more consistent. Individuals with small lungs may be labeled as having false-positive results on the first screening test and therefore may not appear as having false-positive results later. The former applied to every screening test, whereas the latter only applied to the first screening interval. This clarification allows the total cross-sectional specificity to remain unchanged but models serial application screening more effectively. Sensitivity is represented by the transition probability from early disease to identified.

Impact of Screening

Next, the impact of screening was evaluated using the default values for sensitivity. To do so, the transitions from healthy to false positive and from early disease to identified can only occur in months when screening is performed (*eg*, at intervals of 6, 12, or 24 months). Figure 2*D* illustrates the time course of state transitions for a moderate-risk population with a 6-month screening interval. Figure 3 shows the final distribution of workers for four different screening intervals (6, 12, and 24 months, and no screening) for each of the four risk categories. The stacked bars represent the proportion of persons in each of the five outcome categories. In all risk categories, false-positive results become more frequent as the frequency of screening increases, particularly among low-risk individuals. Short-interval screening has the greatest benefit for early detection in the high-risk individuals, but even infrequent screening dramatically reduces the prevalence of both advanced and early disease in persons in the high-risk categories. Results suggest it is unlikely that there would be a single optimal screening interval; rather, it is dependent on the risk category.

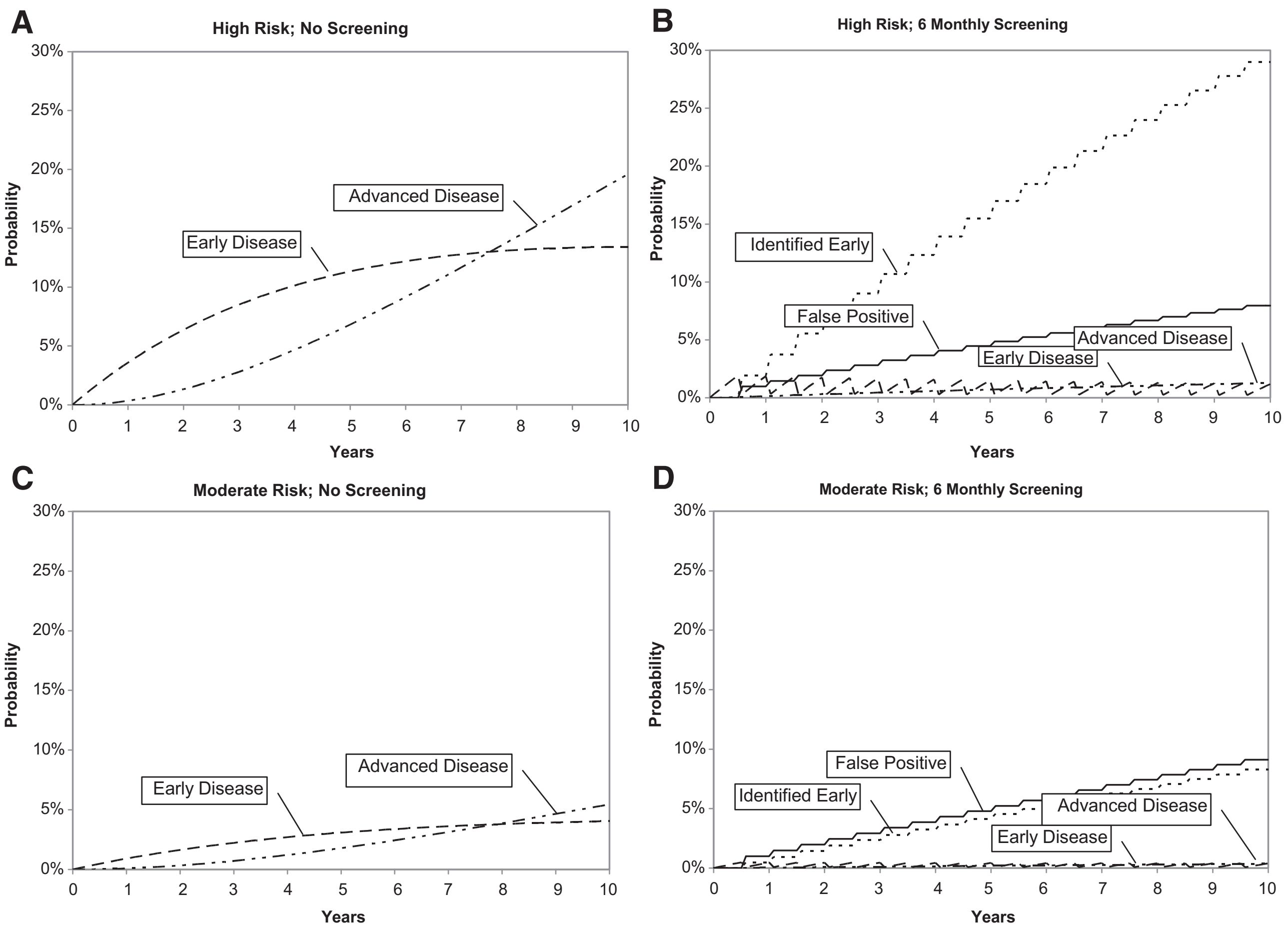

FIGURE 2. Results of basic model distribution among states over time. The figure illustrates the distribution over time among the possible states in the absence of screening (early disease, advanced disease) and with screening (false-positive result and identified early in addition to the other states) with a screening interval of 6 months using default parameters. Probability refers to the likelihood of being in each of the states.

Utility Values

The next step considered the real-life impacts of each of the states, assigning "utility values" to each to reflect its relative benefit or adverse impact. A single category may have different utilities depending on the worker's circumstances (*eg*, it may be beneficial if it leads to compensation but very adverse if it leads to job loss). Utilities were assigned for different sets of circumstances. For purposes of these calculations, sets of utility values were chosen on an *a priori* basis, scaling by assigning a value of + 100 to a healthy working individual and a value of −1,000 for extremely severe advanced disease. Intermediate values were proportional within this range. Table 3 shows several illustrative sets of values. Utilities were assigned for different circumstances. Default values employed a range from −100 for advanced disease to + 100 for being healthy and employed; a slight decrement in utility was assigned for having early undetected disease because there may be subtle subclinical manifestations. Persons with false-positive results were assigned a value of 90, assuming that many would not be subject to job loss if they were referred to occupational pulmonary medicine specialists and properly identified as "nondiseased" using in-depth diagnostic methods such as high-resolution CT scans. The utility for the identified early state was also positive on the assumption that many persons would be given alternative, nonexposed jobs. A different set of utilities was assigned for the "Job Loss" scenario, in which persons identified as positive, whether correctly or incorrectly, lose their employment. The "Protect" scenario reflects a public health/regulatory enforcement perspective, in which the reported presence of disease (persons with early detection and false-positive results) may have a positive societal value by encouraging enforcement. The term "severe" refers to the scenario in which the health outcome is extremely adverse (*eg*, potentially fatal or requiring transplantation).

To simplify the illustrations, utility values were only assigned to the terminal (10-year) distribution.

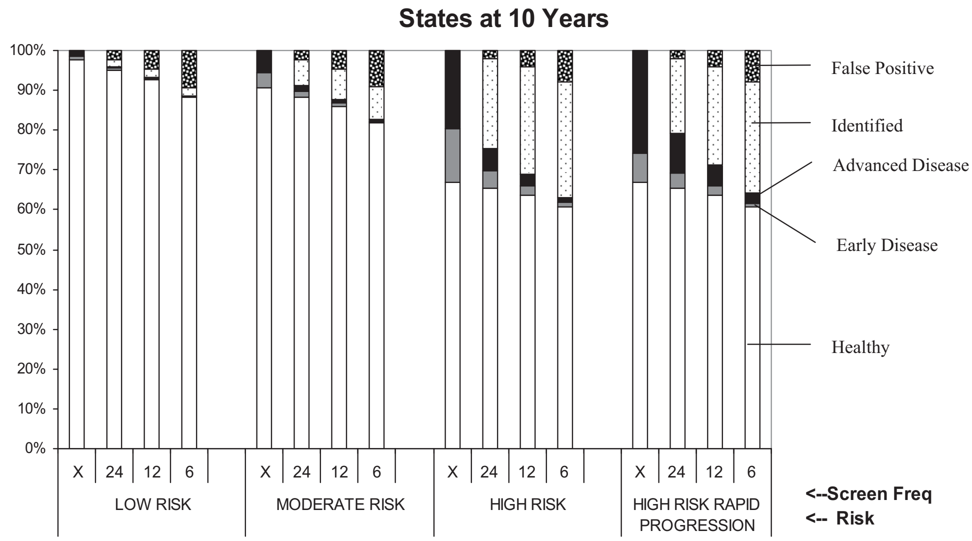

FIGURE 3. Final distribution among outcome states by screening interval and disease risk. For each of 16 combinations of screening interval (6, 12, and 24 months; none [X]) and risk (low, moderate, high, and high-rapid), the figure shows the proportion in each category.

(However, calculations were also performed in which interval utilities were assigned each month and were totaled over the 10-year time horizon; results were generally comparable.) The total 10-year utility was calculated for each combination of utility sets, screening interval, and risk level by multiplying the number of individuals in the state at 10 years by the relative utility assigned to the state. Table 4 sums up the results. In all risk categories, the net utility with screening is better than that with no screening, and the effect is greatest in persons who are in the higher risk categories.

Overall, it appears that a screening interval other than the annual testing is optimal under several sets of conditions. More frequent screening becomes particularly important for higher risk individuals and when there is rapid progression from early to advanced disease. The utility perspectives have great impact on the optimal screening interval. The utility of the false-positive state, which varies from extremely negative to extremely positive among the realistic scenarios, has the major impact on the optimal screening interval; for example, in the job loss scenario, increased screening is associated with more adverse overall outcomes.

Table 3—*Utility Value Sets*

Utility	Relative Utility			
	Default	Job Loss	Protect	Severe
UHE	100	100	100	100
UED	95	95	95	95
UIE	85	−60	150	−10
UAD	−100	−100	−100	−1,000
UFP	90	−60	100	75

The table shows four examples of sets of relative utilities for each of the outcome states. For example, in the Job Loss scenario, in which persons lose their employment if the test result is positive, strongly negative utilities are assigned for false-positive and early detected cases. Further details are in the "Results" section of the text. UHE = utility healthy exposed; UED = utility early disease; UIE = utility identified early; UAD = utility advanced disease; UFP = utility false positive.

Interpretive Paradigm: Longitudinal Criteria

The interpretation of normal spirometry findings is generally based on comparing the individual's result to the distribution of spirometry results in a putatively healthy population. In an alternative paradigm, interpretation may be based on calculating the trend over time within the individual (*ie*, calculating the rate of decline). To illustrate the effects, longitudinal interpretation was compared to a realistic "typical" cross-sectional interpretation situation (80% sensitivity and 0.5% false-positive results due to test noise) and to "specific" cross-sectional interpretation. There is a tradeoff between optimizing specificity and sensitivity, so that the highly specific spirometry (only 0.125% false-positive results) is associated with lower sensitivity (70%). Because longitudinal interpretation typically requires a minimum of several years of data to estimate slope, the traditional cross-sectional approach was used for the first 4 years, whereupon time-variant improvement in the sensitivity and specificity was incorporated. Empirical studies[1,20,21] have shown that the pattern of technical improvement of test performance over

Table 4—*Impact of Social Circumstances Upon Long-Term Benefit*

Risk	Scrn Freq	Cumulative Utility at 10 yr: Default	Job Loss	Protect	Severe
Low risk	6	98.5	81.3	100.9	94.2
	12	98.8	88.7	100.6	94.3
	24	98.7	92.6	100	93
	None	97.1	97.1	97.1	84.5
Moderate risk	6	97.1	71.4	103.4	84.5
	12	96.7	78.6	102.2	81.5
	24	95.5	82.8	99.9	74.8
	None	88.9	88.9	88.9	39.8
High risk	6	92.2	38.2	111.9	51.9
	12	89.8	44.5	107.8	38.2
	24	85	49.3	99.8	12.7
	None	60.1	60.1	60.1	−116.2
High risk with rapid progression	6	89.9	37.7	108.8	39.6
	12	85.1	43.2	101.6	13.1
	24	76.7	46.4	89.1	−31.7
	None	48.1	48.1	48.1	−183.7

This table compares the overall impact (cumulative utility at 10 years) according to screening frequency for the different risk levels and social circumstances (using the utility values shown in Table 3). Scrn Freq = screening intervals (6, 12, 24 months), and no screening (none).

time is statistically complex; we used a simple algorithm with improvement in sensitivity and specificity logarithmically related to the number of testing episodes to date (*eg*, at any screen, performance would be better with semiannual testing than with biannual testing).

Table 5 estimates the effect outcomes at 10 years for the several risk/screening interval conditions. Figure 4 compares the total utility for moderate-risk and high-risk rapid progression using 6- or 24-month screening intervals using default utilities. The impact of screening interval was greater than the differences due to interpretive strategy per se. However, longitudinal interpretation was preferable, particularly with higher risk (*ie*, high-risk and high-risk-rapid progression). The number of false-positive results with cross-sectional screening was greater than that with longitudinal interpretation, particularly with frequent screening in comparison to screening at 24-month intervals (results not illustrated).

Discussion

This article describes an analytic approach to answering the apparently simple question, "How frequently should workplace spirometry be performed?" In addition to use for assessing individual patients presenting with symptoms, spirometry is an effective workplace surveillance tool, benefiting both individual workers and public health.

Our analysis uses workplace spirometry screening for diacetyl as an example, but the principles are applicable to those of spirometry screening for other occupational hazards and perhaps for workplace screening in general. Diacetyl is a low-molecular-weight chemical widely used as a flavoring agent; it has been associated with fixed airflow obstruction and bronchiolitis obliterans.[9,10,12,18] Data[7] indicate that removing workers from exposure can limit the progression to advanced disease. Furthermore, progression from normality to advanced airflow obstruc-

Table 5—*Comparison of Longitudinal and Cross-Sectional Interpretation Strategies*

	Moderate Risk						High Risk to Rapid Progression			
	6 mo		12 mo		24 mo		6 mo		24 mo	
Risk	L	C	L	C	L	C	L	C	L	C
Healthy exposed	86%	82%	87%	86%	89%	88%	64%	61%	66%	65%
Early disease	0%	0%	1%	1%	2%	1%	1%	1%	4%	4%
Identified	8%	8%	8%	8%	6%	6%	28%	28%	18%	19%
Advanced disease	0%	0%	1%	1%	2%	2%	3%	3%	11%	10%
False-positive	5%	9%	3%	5%	2%	2%	4%	8%	2%	2%

The distribution among states at 10 years for longitudinal and cross-sectional interpretive strategies for moderate risk and high risk with rapid progression situations and screening intervals of 6, 12, and 24 mo. L = longitudinal interpretive strategy; C = cross-sectional interpretive strategy.

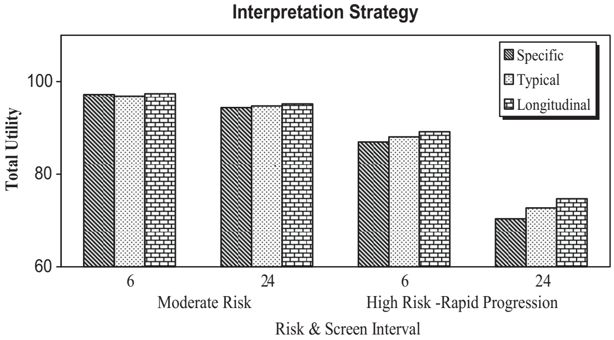

FIGURE 4. Effect of interpretation strategy on utility. The figure shows the impact of interpretation strategy (longitudinal vs cross-sectional) on total utility at 10 years. The screening intervals shown are 6 and 24 months. The risk categories moderate risk and high risk, and rapidly progressive are shown. "Specific" refers to high-quality spirometry with an interpretive strategy seeking to limit false-positive results, and "typical" refers to usual spirometry quality in workplace settings.

tion can occur within several years. Diacetyl-related fixed airflow obstruction is known to progress more rapidly than obstruction due to many other occupational exposures.

The analysis used a Markov chain model.[22–24] With this widely used method, a series of discrete health states is defined, and each individual within a state has a defined probability of transitioning to another state in any time period (*eg*, from healthy to early disease). Progression of a population among states over time is analyzed; the effect of varied assumptions and interventions can be incorporated into the models.

Our analysis demonstrated there is no single answer to the optimal screening frequency. Factors that should inform the decision include the following.

Risk of disease markedly affects the choice of screening intervals. The extent of exposure is a major determinant of the risk of diacetyl-induced disease. Frequent screening may be disadvantageous for workers with low exposures but may be very beneficial for those with high diacetyl exposure.

Screening seeks to identify individuals with early disease before symptoms are sufficiently advanced that the patient would otherwise seek medical care. The natural course significantly affects the screening utility. More frequent screening is necessary to identify early cases when progression from early to late disease occurs quickly. Unfortunately, most epidemiologic studies, particularly cross-sectional studies, are unable to provide adequate information about the "preclinical" stages of many diseases. However, as shown in Table 2, reasonable ranges for otherwise unobservable parameters may be defined by comparing the implications of different sets of progression parameters.

The perceived utility values (*ie*, benefit or adversity) of each clinical state (*eg*, false-positive or advanced disease) have considerable impact. For example, identification as an early case may have minimal adverse impact if an alternative unexposed job is immediately available; conversely, it may be extremely adverse from the worker's perspective if it leads to unemployment. Persons with false-positive results, that is, individuals incorrectly identified as having disease, accrue no medical benefit by identification but could potentially be subject to adverse employment or insurability consequences.

Test performance characteristics are also important. Traditionally, the cut point for defining "normal" spirometry results is chosen so there will be 5% false-positive results.[6] Although this may be acceptable for clinical testing on a single occasion, this could lead to many false-positive results when testing is performed repetitively on the same individuals. Analysis suggested delineating the following two distinct causes of false-positive results: inherent population variability reflects biological differences even among healthy individuals; test noise, however, reflects a lack of precision of the testing procedure. In our model, test variability due to noise applied each time spirometry was conducted, whereas population-based biological variability occurred only at the first testing episode. Properly conducted spirometry can significantly reduce but not completely eliminate the imprecision (noise) of testing.[25,26]

In addition to the inherent characteristics of the populations and spirometry testing procedures, intentional programmatic choices can affect the sensitivity and specificity of testing. Choosing a cut point with high sensitivity (*eg*, identifying persons with $FEV_1 < 90\%$ predicted as abnormal) will be associated with low specificity, whereas minimizing false-positive results leads to lower sensitivity. In decision analysis, as often expressed by receiver operating characteristic curves, the criterion for defining a positive test result depends on the utility value (weighing the consequences) associated with true-positive and false-positive results.

The paradigm used for interpreting spirometry is also a significant factor. Generally, a single individual's FEV_1 test result is compared to the distribution of test results from a "normal" population. This single-test cross-sectional approach is fundamental to both clinical practice and workplace testing mandated by the OSHA regulations. Although logical for a single patient visit, interpretation using a cross-sectional paradigm does not benefit from prior test results from the individual. Longitudinal interpretation has been suggested as a significant improvement.[1,20,21,27,28] Longitudinal analysis determines the trend over time of an individual's test results, and abnormality is defined by a more rapid rate of decline of FEV_1. Theoretically, this approach may reduce the impact of biological variability because the individual's results are compared to his or her own prior data rather than to data from a large heterogeneous population. Longitudinal analysis may be particularly effective at detecting early disease in workers whose baseline spirometry values are considerably above average (*eg*, a drop from 120 to 90% predicted would raise concern in a longitudinal assessment but would not be detected in a cross-sectional analysis). However, longitudinal analysis has several potential drawbacks. Generally, several years of data are required to estimate the slope meaningfully, although occasionally a very large interval drop identifies a worker who is at risk. Furthermore, the number of false-positive results may be greater because the magnitude of the signal is smaller than for cross-sectional analysis (*eg*, 25-mL excess loss per year implies doubling of the normal rate of decline). In addition, there is no consensus about the optimal method of calculating the rate of decline.[20,21] Our analysis suggests that longitudinal analysis has a marginal benefit when applied to high-risk situations. Hence, each of these factors should be carefully considered when choosing the optimal screening frequency.

Benefits of Decision Modeling

Decision analysis has been applied to optimizing occupational asthma screening.[29,30] Decision-modeling techniques offer several advantages. First, establishing a model requires explicitly delineating factors requiring consideration.[22] Particularly for decisions affecting public policy (*eg*, OSHA-mandated testing), explicit and transparent decision making is facilitated. For example, the magnitude of the risk should not in itself determine more frequent testing. Frequent testing for diacetyl-exposed workers is supported by the availability of a very effective preventive intervention (removal from exposure or workplace exposure control). Conversely, the limited utility value of early detection and the negative utility of false-positive results may constrain the value of short-interval lung cancer screening.

Second, decision modeling can directly define the optimal solution. The current analysis suggests that workplace screening for diacetyl-exposed workers should be done more frequently than annually, particularly for those persons in high-exposure situations. Reliance on annual or less frequent screening appears likely to be suboptimal.

Third, decision modeling can inform research priorities. By identifying uncertainties that have significant impact on clinical and public health decision making, research can be appropriately focused. In the diacetyl example, prospective studies of the natural course of the disease and meaningful studies of the economic implications of early identification probably warrant higher priority than a large number of additional studies of cross-sectional prevalence.

Limitations

The analysis employed a Markov chain model. This widely used technique assumes, however, that risk applies homogeneously to all individuals within a particular state. However, there probably are significant differences in personal susceptibility to disease development as well as differences of the personal impact (*ie*, utility) of each outcome state. These calculations were based on the "average person." Although not included in the current model, the approach can be extended by incorporating a stochastic modeling technique such as a Monte Carlo simulation reflecting random variation. Parameters for the model were estimated from the available literature, but the epidemiologic and clinical data are incomplete. However, it was possible to identify reasonable ranges for values by excluding parameters that would lead to results incompatible with the limited empirical data.

The model used an arbitrary 10-year time horizon. Alternative time frames might lead to different results. For example, longer time spans increase the precision of longitudinal slope estimates. The tenure of the typical worker in the industry should help inform the time horizon chosen for analysis. Once the model is established, calculations can easily be performed for other time spans.

The utility values employed were chosen for illustrative purposes. Optimally, utility values should be ascertained by directly surveying stakeholders about their values. In addition to the preferences of the stakeholders (*eg*, workers, insurers, and public health officers), formal economic data about the implications would be helpful. The current model considers only the utility of each of the states and does not directly consider the cost of establishing a spirometry program. However, this model approach could be extended to permit a cost-effectiveness analysis by including estimated cost data.

Summary

The study demonstrates that an apparently simple question, "How often should workplace spirometry be performed?," requires the careful delineation of significant factors. Annual testing may be appropriate in some settings, but in other diacetyl-exposed settings more frequent spirometry testing may be advisable.

The interpretation of workplace spirometry data using longitudinal rather than cross-sectional paradigms is potentially useful, particularly in patients with rapidly progressive disorders, but requires validation.

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