Sustaining SBIRT in the wild: simulating revenues and costs for Screening, Brief Intervention and Referral to Treatment programs

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Abstract:

Aims: To examine the conditions under which Screening, Brief Intervention and Referral to Treatment (SBIRT) programs can be sustained by health insurance payments. **Design:** A mathematical model was used to estimate the number of patients needed for revenues to exceed costs. **Setting:** Three medical settings in the United States were examined: in-patient, out-patient and emergency department. Components of SBIRT were delivered by combinations of health-care practitioners (generalists) and behavioral health specialists. **Participants:** Practitioners in seven SBIRT programs who received grants from the US Substance Abuse and Mental Health Services Administration (SAMHSA). **Measurements:** Program costs and revenues were measured using data from grantees. Patient flows were measured from administrative data and adjusted with prevalence and screening estimates from the literature. **Findings:** SBIRT can be sustained through health insurance reimbursement in out-patient and emergency department settings in most staffing mixes. To sustain SBIRT in in-patient programs, a patient flow larger than the national average may be needed; if that flow is achieved, the range of screens required to maintain a surplus is narrow. Sensitivity analyses suggest that the results are very sensitive to changes in the proportion of insured patients. **Conclusions:** Screening, Brief Intervention and Referral to Treatment programs in the United States can be sustained by health insurance payments under a variety of staffing models. Screening, Brief Intervention and Referral to Treatment programs can be sustained only in an in-patient setting with above-average patient flow (more than 2500 screens). Screening, Brief Intervention and Referral to Treatment programs in out-patient and emergency department settings can be sustained with below-average patient flows (fewer than 125 000 out-patient visits and fewer than 27 000 emergency department visits).

Keywords: cost | health insurance | revenue | SBIRT | screening and brief intervention | simulation | sustainability

Article:

Introduction

Screening and Brief Intervention (SBI) has been shown to be a clinically effective service to identify and treat problematic substance use [1]. Screening is based typically on a structured instrument (e.g. the Alcohol Use Disorders Id\=entification Test (AUDIT) (Babor *et al*. [2]). Brief intervention (BI) is any therapeutic or preventive consultation of short duration (one to five sessions) undertaken by a health-care professional [1, 3]. It is often provided in non-specialty settings and typically comprises assessment, feedback, advice and the provision of information and self-help materials [4]. Most of the SBI literature focuses on hazardous users of alcohol (see Heather *et al*. [5]), defined typically as people who consume above recommended guidelines for safe consumption but who would not be considered dependent. Recent innovations in SBI include adding brief treatment (BT) and referral to treatment (RT) for people at the upper end of the risk continuum and for people suspected of meeting criteria for dependence [6].

A number of organizations in the United States have received competitive federal grants to initiate programs that deliver a combination of SBI, BT and RT, otherwise known as SBIRT. Among these were a cohort of grantees who received funds in 2005 from the Substance Abuse and Mental Health Services Administration (SAMHSA) to deliver SBIRT. This study uses a simulation to model the conditions under which SBIRT would be self-sustaining when relying upon public and private insurance coverage that covers only some patients. A simulation model necessarily simplifies the complexities of reality to a core set of features. Reducing patient and service provider heterogeneity ensures that commonalities are captured and helps to generalize the findings.

To determine whether a program can be sustained financially requires understanding of its revenues and costs. Funding and revenue clearly affect substance abuse programming [7], but only a few studies have been published on this topic. The studies on funding and revenue examine substance abuse treatment generally, rather than SBI or SBIRT in particular. Recent topics include describing funding trends [8], discovering and navigating funding sources [9], setting reimbursement to be commensurate with cost bands [10], assessing the relationship between funding source and credentialing [11] and understanding the impact of managed care on treatment [12].

To our knowledge, no published study on SBIRT has estimated costs across multiple sites of service. A recent review suggests that the literature on the cost of SBI is more developed than that on the cost of the SBIRT program [13]. The review also indicates that the estimates of SBI costs vary substantially [14-25]. Some of the cost variation is probably attributable to differences in staffing (e.g. doctor versus behavioral health counselor) and setting [e.g. emergency department (ED) versus out-patient clinic] [26].

The current study assesses the conditions under which SBIRT is sustainable without SAMHSA grant funding—that is, SBIRT 'in the wild'. For our purposes, sustainability is achieved when revenues meet or exceed costs. The study focuses on variables that providers of SBIRT most commonly face—patient flow and the number and type of staff hired to provide services to those patients—and these variables are key to the research question examined: under certain staffing mixes, how many screens must be performed to make the program sustainable? The results provide clear guidance on suggested staffing for given numbers of screens and the degree to which sustainability would be affected by varying numbers of screens. Because the findings are of direct practical relevance, they may help SBIRT providers and decision-makers to plan resources appropriately.

Methods

Setting

During a 5-year period, SAMHSA funded SBIRT operations within an initial cohort of seven grantees: California, Cook Inlet Tribal Council in partnership with the Southcentral Foundation in Alaska, Illinois, New Mexico, Pennsylvania, Texas and Washington. The SBIRT programs varied both within and across grantees in terms of service setting and staff training and qualifications, but all delivered the same core set of SBIRT services: screening, BI, BT and RT. In addition, in many locations pre-screening was conducted to screen out more efficiently individuals with little to no risk. Grantees implemented SBIRT in a wide range of health-care settings, including in-patient hospitals, EDs/trauma centers and a variety of ambulatory care clinics, such as hospital out-patient clinics. Most staff providing BT services had a degree beyond the bachelor or baccalaureate level, such as a master's degree in counseling (67%). More than 70% of the SBIRT providers were female, and approximately one-third were Hispanic. Approximately 50% of those providing screening and BI services and more than 7% of those providing BT services were certified currently or previously in addiction treatment.

SBIRT was examined separately by the medical setting in which services were provided: in-patient, out-patient and ED. The programs are categorized by (a) whether the provider organization employed the staff delivering SBIRT ('in-house') directly or contracted with them, and (b) whether the staff were generalists or specialists. Generalists are typically physicians, nurses or medical assistants who perform other medical services within the host setting. Specialists are trained in the fields of alcohol or substance abuse and are qualified behavioral health counselors, social workers, health educators or psychologists. Evidence from visits to and interviews with four of the seven original SAMHSA grantees after their funding had ended suggested that SBIRT service delivery relied upon a mix of in-house generalists and contracted specialists, and the current study followed this delivery model. Generalists typically conducted pre-screening, screening and the first BI. Specialists also delivered these services when they were not supporting other SBIRT activities. Typically, only specialists delivered subsequent BI sessions, BT and RT.

The current study was part of a cross-site evaluation that assessed the SBIRT process (including adherence to the evidence base in service provision), estimated the costs of services and provided administrative data on the number of clients referred to services. The task assessing adherence to the evidence base provided the following findings on which pre-screens and screens were implemented across grantees. Five grantees had pre-screening protocols using one of three approaches for alcohol: (1) the AUDIT-C (validated by Bradley *et al*. [27]); (2) a non-evidence-based two-step combination of a question on how recently a patient drank more than four drinks on an occasion screening into the second step of the full AUDIT; and (3) three questions on alcohol [28]. For drugs, none of the five grantees using a pre-screen protocol used one that was evidence-based. The pre-screen questions varied, comprising three to five questions; one grantee, for example, used questions from the Texas Christian University (TCU) Drug Screen II [29]. All grantees had evidence-based protocols for alcohol misuse. Six of the seven grantees used the AUDIT and the seventh switched midway through the evaluation period from the AUDIT to the Alcohol, Smoking and Substance Involvement Screening Test [30]. Grantees were required to screen for illicit drug use and five of the seven were evidence-based. Of these, four used the 10-question version of the Drug Abuse Screening Test [31] and a fifth used the full TCU Drug Screen II [29].

Data

The core data for the simulation model parameters were from the larger cross-site evaluation project and published reimbursement rates [32] (see Table 1). Supporting information, Appendix S1 provides additional parameter estimates and their sources. When parameter values were assumed, they were informed by findings from a separate task assessing the process of implementing SBIRT as part of the parent project of the current study, correspondence with experts and stakeholders or direct observation. Labor utilization, space utilization and cost estimates were obtained as part of the parent project. Cost data included costs that varied by the number of patients served (variable costs) and costs that varied only by the number of staff hired, but not by the number of patients *per se* (quasi-fixed costs).

Table 1. Values and sources for model parameters.

Parameter	*Values*
Parameters governing costs	
Average length of service (minutes)	
Screen	3.9–13.8[a]
Brief intervention (BI)	12.2–21.6[a]
Proportion of screening + BI longer than 30 minutes	0.14–0.25[a]
Brief treatment (BT)	40.3–52.4[a]
Referral to treatment (RT)	4.5–27.3[a]
Costs	
Quasi-fixed costs/administration and training (annual)	$5797–$22,360[a]
Space utilization for service delivery (feet^2)	70–224[a]
Labor costs ($/hour)	$25.52–$38.61[a]
Specialist salary (annual)	$53 020–$54,981[a]
Parameters governing reimbursement	
Probability of being covered by any insurance	0.495
P (Medicaid)	0.67[b]
P (private insurance)	0.33[b]
Reimbursement amount	
Private insurance	

Parameter	Values
Screening and BI; 15–30 minutes	$33.41[c]
Screening and BI; more than 30 minutes	$65.51[c]
Medicaid	
Screening	$24.00[c]
BI, per 15 minutes	$48.00[c]
Parameters governing number of patients served	
Ratio of pre-screen to screen	3.14
Ratio of BI to screen	0.242–0.373[d]
Ratio of BT to screen	0.076–0.117[d]
Ratio of RT to screen	0.064–0.098[d]

Data sources are estimates from study data unless noted otherwise.
[a] Value depends on setting and service provider;
[b] value is assumed;
[c] value does not vary by risk level—source: SAMHSA [32];
[d] value depends upon whether a pre-screen is used.

Constructing the model

The model captures the essential financial characteristics of SBIRT provision without grant funding in a program that is fully implemented with re-screening for patients on a twice-yearly or yearly basis. Every service involves staff time and thus incurs a cost and, depending on patient insurance coverage, most service events generate revenue. Service events are modeled as conditionally independent, following the precedent in the literature on decision analysis modeling [34].

In addition to including the core SBIRT components and modeling transitions between them, the model includes many real-world details pertinent to determining SBIRT revenue and costs. Because the model allows pre-screens and screens to result in false positives, for example, screens are not only admininstered to patients who pre-screen positive for hazardous use but also to patients who are false positive pre-screens. Importantly, the SBIRT program incurs the costs of generalists only when they are performing SBIRT activities, whereas it incurs the cost of a specialist at all times; and either generalists or specialists may deliver screening and the first BI, but only specialists deliver follow-up BI, BT and RT. Also, following reimbursement guidelines at the time of the study, pre-screens were assumed to be not reimbursable under private or public insurance [32].

The model includes several simplifying assumptions, and most of these apply to four sets of parameters. Assumptions about the first three—percentage of people being screened, certain types of costs and reimbursement—reflect data limitations. With regard to the percentage of people being screened, the available data did not separate the counts of pre-screens from screens. Without adjusting for this limitation, the estimated percentage screening positive would be artificially low. The proportion screening positive was adjusted by using the 2002–08 waves of NSDUH to estimate the proportion of adults aged 18–64 years likely to qualify as hazardous substance users and then combining that proportion with estimates from the literature on the sensitivity and specificity of screening and pre-screening instruments. The model assumed values for quasi-fixed costs, which are costs that vary by the number of staff employed, as opposed to costs that never vary (fixed costs) or costs that vary on a per-patient basis (marginal costs). Also, because the program is implemented fully, start-up costs are omitted. Two assumptions were needed regarding parameters on reimbursement, and both result from the fact that many SBIRT providers are public, not-for-profit organizations that serve a large proportion of low-income patients and rely upon Medicaid for funding. The data and evidence did not provide definitive guidance on out-of-pocket payment amounts or the proportion of patients covered by Medicaid. The model assumes no out-of-pocket payment. The proportion of patients covered by Medicaid was varied in sensitivity analyses, as described below.

The final and fourth set of assumptions was with respect to staffing. The model assumes that specialists can spend up to 80% of their time delivering services generally, and the remaining 20% or more of their time is spent in activities such as meetings, training or quality assurance tasks. Of the 80% of specialists' time spent on service delivery, up to 50% can be spent on follow-up BI, BT and RT. Of the remaining time, 30% or more is spent performing pre-screening, screening and BI or in non-productive activities. These assumptions help to ensure that the model can be solved and its findings interpreted. An alternative to making these assumptions was to model phenomena explicitly, such as temporal variation in the number of patients presenting for pre-screens, but this increases modeling complexity significantly.

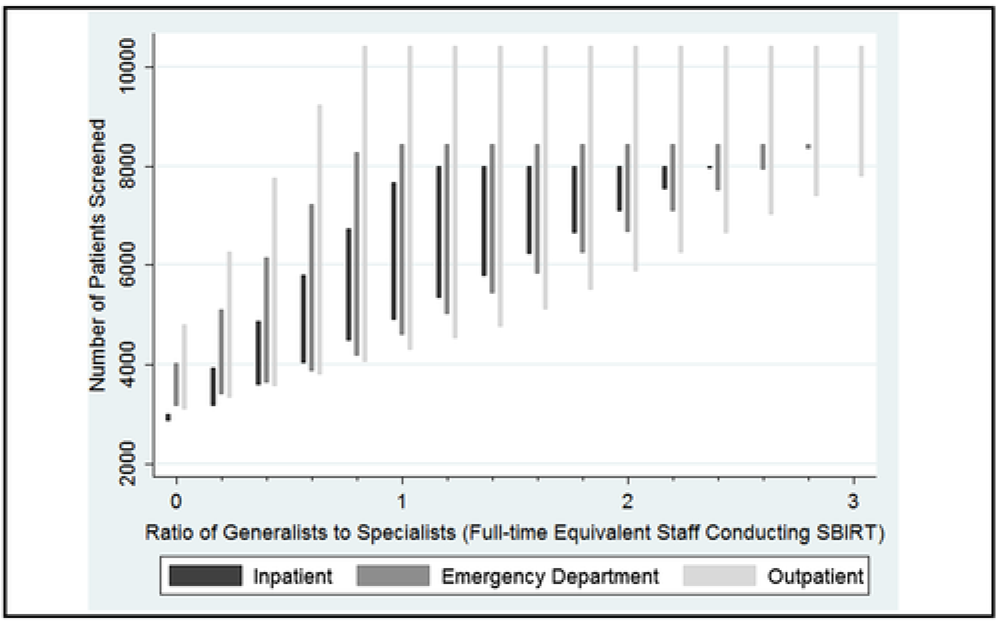
Sensitivity analyses were conducted to examine the impact of changes in important parameters upon study conclusions. For these analyses, two sets of parameters were varied. The first set of parameters determined the probability of a patient being covered by Medicaid and the probability of a patient being covered by private insurance; these two probabilities were varied in increments together. The second set concerned the quasi-fixed administrative cost. The hypothetical staff composition was set at levels that would be feasible for a typical program: no generalists and one specialist in the in-patient setting and three generalists and one specialist practitioner in the out-patient setting.

Solving the model

The model was solved mathematically to simulate an administrator choosing the number of generalist and specialist staff to provide SBIRT to as many patients as possible. This choice is subject to three constraints. First, reimbursement must equal or exceed total cost. Secondly, the number of patients whom generalists can screen in a period is constrained by the total amount of time that generalist and specialist practitioners have available to see patients. Thirdly, specialist time is prioritized to deliver services that generalists cannot provide: follow-up BI, BT and RT. This constraint therefore limits the number of patients who specialists can screen to however many can be scheduled after specialists have delivered specialty services. Supporting information, Appendix S2 shows the constraints and solution mathematically.

Results

Figure 1 shows, by setting, how many screens per year are needed to sustain an SBIRT program financially when holding constant the number of specialists at one and varying the ratio of generalists who deliver one or more SBIRT services to that specialist. Because the model allows for some flexibility in the amount of generalists' time used to deliver SBIRT, the measure of generalists in the figure sets a ceiling that is operationalized in blocks of 20% of a full-time equivalent employee. Five generalists is operationalized as five separate people spending up to 20% time. Because every additional generalist used to deliver SBIRT incurs a relatively small quasi-fixed administrative cost, using five generalists costs slightly more than using one full-time person with the same salary. Thus, configurations of generalists where more than 20% of a person is used would require slightly lower patient flow than that reported in Fig. 1. Also, in analyses not shown, when the number of specialists is fixed at a higher number than one, the pattern of sustainable ranges remains the same across settings and the overall pattern shown shifts up the vertical axis. Supporting information, Appendix S3 contains the estimates used to construct Fig. 1 and results for other counts of specialists.



Notes: The financially sustainable range of screened patients is shown by the vertical bars. Generalist staff are counted in blocks of 0.2 of a full-time equivalent. As more specialists are added, the pattern of bars shifts up and to the right.

Figure 1. Number of pre-screened patients needed to financially sustain Screening, Brief Intervention and Referral to Treatment (SBIRT) by the ratio of generalist to specialist staff conducting SBIRT: findings for one specialist

Figure 1 shows at least three major findings. First, it indicates considerable variation across settings in the range of the number of patients pre-screened who can be sustained financially. At zero generalists and one specialist, for example, the range of screened patients in SBIRT that can be sustained in an in-patient setting is very small—between 2852 and 2995, or 143 patients. Screening fewer than 2852 patients does not yield enough reimbursement to cover costs; capacity constraints mean screening more than 2995 patients cannot be served with one specialist. The range is greater in the ED/trauma setting and greatest of all in the out-patient setting.

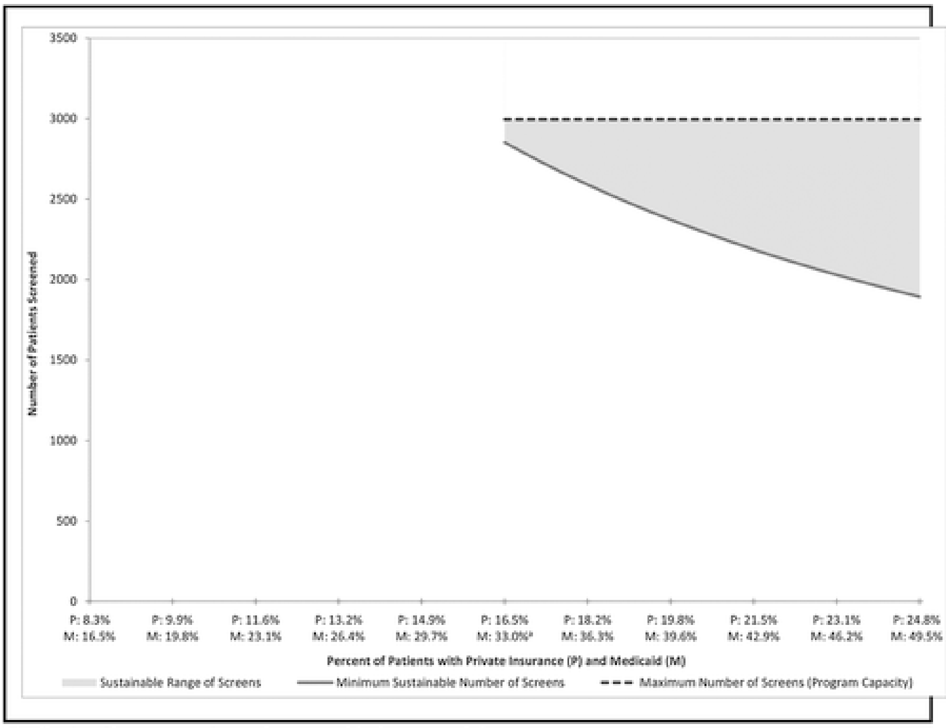
The second major finding is that the size of the sustainable range of patients screened increases considerably as more generalist time is combined with a given specialist. For example, a ratio of 1:1 requires between 3147 and 3931 patients (a range of 784) for it to be sustained financially in an in-patient setting. Note also that, even though the range increases with the ratio, the minimum number of patients screened in that range also increases.

A third major finding is that in the in-patient setting the sustainable staffing mix is very sensitive to the ratio of generalists to specialists, whereas in the out-patient setting there is less sensitivity. This finding is illustrated by comparing, across settings, the amount by which the top of one bar is higher than the bottom of the bar to its right for that setting. More bars overlapping means that more combinations of staffing ratios can be used to sustain a given number of patients screened, and a larger degree of overlap between any two bars means that a given staffing ratio can sustain a larger range of patients screened. For the one specialist case in the in-patient setting, for example, the maximum sustainable number of patients screened with no generalists does not overlap at all with the minimum number of patients screened for any of the higher ratios of generalists. By contrast, in the out-patient setting the maximum sustainable number of patients screened at zero generalists is higher than the minimum number of the next six bars for that setting—up to 1.2 blocks of 20% of a generalist full-time equivalent for every specialist. This finding means that in the in-patient setting there are relatively few sustainable generalist to specialist staffing ratios, whereas in the out-patient setting there are many more options.

The exceptions to these broad findings are staffing mixes with a large proportion of generalists. In estimates not presented, for example, a mix of 13 generalists and one specialist in an in-patient setting is not sustainable at all. For these staffing mixes, the specialist on staff cannot support enough additional patients with follow-up BI, BT and RT, and thus many patients would not be provided services.

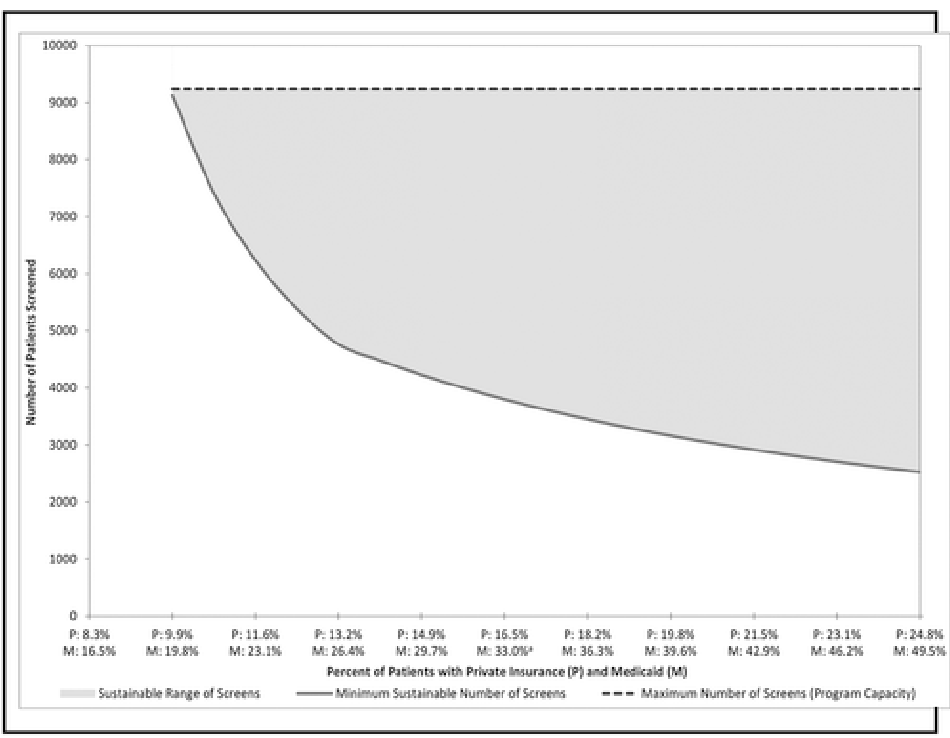
Figures 2 and 3 highlight the impact across a hypothetical range of proportions of people covered by private insurance and Medicaid on the sustainable range of screens. The staffing mix is zero generalists implementing SBIRT and one specialist in the in-patient setting (Fig. 2), and three generalists implementing SBIRT and one specialist in the out-patient setting (Fig. 3). The sustainable range of screens is represented by the shaded region, which is bounded by the minimum number of patients that the program must screen annually to break even and the maximum number of patients that a program with three generalists and one specialist can screen in a year, given their time constraints.

The figures show the range of sustainable screens widening as the proportion of patients who are insured increases. In the in-patient setting (Fig. 2), the proportions of people with insurance coverage—16.5% for private insurance and 33.0% for Medicaid—leads to a range of sustainable screens that is quite narrow, between 2850 and 3000 (a range of 150 screens). The range broadens considerably to approximately 1200 screens as the proportion of insured patients rises to the case where nearly 25% are insured privately and nearly 50% are under Medicaid. In the out-patient setting (Fig. 3), the range of sustainable screens broadens from approximately 5000 at the given proportions covered by insurance (16.5% private, 33% Medicaid) to 6000 at the proportion shown (25 private, 50% Medicaid).



[a] Indicates the parameter values used in base model.

Figure 2. Effect of varying annual proportion of patients covered by insurance on sustainable annual ranges of patient screens: Screening, Brief Intervention and Referral to Treatment (SBIRT) in in-patient setting with one specialist but no generalists providing SBIRT



[a] Indicates the parameter values used in base model.

Figure 3. Effect of varying annual proportion of patients covered by insurance on sustainable annual ranges of patient screens: Screening, Brief Intervention and Referral to Treatment (SBIRT) in out-patient setting with one specialist and 60% of a generalist full-time-equivalent providing SBIRT

Comparing the two figures illustrates further that, under the model conditions, sustaining in-patient programs may be more difficult than sustaining out-patient programs. In the in-patient setting, the range of sustainable screens at lower levels of patient insurance is narrow. In fact, combining the estimates presented suggests that to sustain SBIRT in an in-patient setting at the given insurance coverage levels (16.5% private, 33% Medicaid), an in-patient program would have to maintain at least 95% capacity (2852 annual screens minimum out of 2995 capacity) to be sustained. The out-patient program would need to maintain only 41% capacity (3799 screens out of a maximum 9236) to be sustained under the same proportion insured. Nevertheless, at the highest proportions of insurance coverage considered (25% private, 50% Medicaid), the sustainable range of screens for the in-patient setting is far broader, at between 1800 and 3000 screens.

Other sensitivity analyses were conducted that varied the quasi-fixed administrative cost, but the conclusions were not affected. Although, in both settings, the maximum surplus decreased when the quasi-fixed administrative cost increased, the effect on program sustainability was far smaller than when adjusting the proportion of patients covered by insurance.

Discussion

Health care is expensive and budgets are limited, so providers and decision-makers need to understand the circumstances under which SBIRT is sustainable without grant funding from government sources. The current study provides evidence on how many patients must be screened to cover SBIRT program costs under fairly typical conditions governing patient insurance characteristics and reimbursement rates in the United States. The evidence draws from a mathematical model that combines the most accurate data sources and estimates available.

The difference across settings in the sustainable range of screens is driven primarily by differences in the amount of time taken to deliver services. Data from the cross-site evaluation indicated that more time is taken to deliver services in an in-patient setting than in an out-patient or ED setting. For example, an average screen and BI takes 35 minutes in an in-patient setting, compared with 24 and 21 minutes in out-patient and ED settings, respectively. In-patient providers are able to serve fewer patients than providers in other settings. In the case of a small SBIRT program with no generalists and one specialist, in-patient practitioners can support only 74% of the patients that a similar program can support in an ED setting and only 63% of the same program in an out-patient setting.

The results indicate that a large variety of configurations of generalists and specialists could be used to run a viable SBIRT program in the out-patient and ED settings. However, meeting patient flow targets may be problematic for the in-patient setting. The higher costs in that setting make the range of screens that can be sustainable relatively narrow. Indeed, the results indicate that SBIRT could be sustained only in an in-patient setting with above-average patient flow. The number of screens in an in-patient setting with average patient flow is approximately 2500. This is derived by combining estimates on the mean number of in-patient discharges in the United States (which is 7686 [35]) with the current model, such as a 3:1 pre-screen:screen ratio and universal pr-escreening. This estimate is lower than the minimum number of screens that can be sustained, according to the results.

Solutions for making SBIRT financially sustainable in the in-patient setting with low patient admissions may focus upon increasing patient flow into the reimbursed services, which follow pre-screen. One blunt solution may be to eliminate pre-screening (which does not receive reimbursement) and institute universal screening. A short screening instrument may be needed to achieve this, such as the AUDIT-C for alcohol. This solution responds purely to reimbursement incentives, however, and ignores the purpose that pre-screens serve, which is to ensure that downstream services are not provided unnecessarily to people who do not need them. An alternative and probably preferred solution for a low-flow in-patient hospital that also has SBIRT practitioners in an ED or out-patient setting is for those practitioners to cover the in-patient setting additionally. Future research is needed to examine the revenues and costs of alternative service configurations in each setting.

In contrast to the in-patient setting, SBIRT in out-patient and ED settings may be sustained with below-average patient flows. The average annual number of visits for hospital-based ED and hospital-based out-patient units are approximately 27 000 and 125 000, respectively [36]. Based on a 3:1 pre-screen : screen ratio, the patient flow estimates translate to 9000 and ~42 000 screens per year, and the results show that these estimates are within the sustainable screen ranges of several staffing combinations for both settings.

The findings shed some light on the importance of health-care reform in the United States. Under the Affordable Care Act (ACA), states may elect to expand their Medicaid eligibility, which is anticipated to increase in particular the number of childless adults covered by Medicaid with incomes up to 138% of the Federal Poverty Level [37]. This expansion is very salient to the SBIRT program, because many grantees serve people who are currently uninsured but will probably qualify and obtain Medicaid under the ACA. Moreover, SBI for alcohol is considered an essential health benefit that will be covered by Medicaid. The results of the current study show that the financial sustainability of SBIRT programs is sensitive to the proportion of patients who are covered by insurance to receive SBIRT services and much less sensitive to changes in quasi-fixed costs. The estimates show that with a high proportion of the population covered by insurance, as may occur with the ACA, SBIRT would probably be sustainable under a large number of staffing mixes in all settings. Simply allowing SBIRT to be reimbursed under Medicaid will greatly aid its ability to be sustained as a stand-alone program.

The promise of Medicaid expansion may not be realized fully. For example, states may choose not to expand Medicaid, Medicaid uptake may be lower than anticipated or SBIRT services might not be covered sufficiently under Medicaid. In such cases, SBIRT programs may choose to seek other sources of funding, such as the federally provided and state-administered Substance Abuse Prevention and Treatment Block Grant. To this end, the results quantify the shortfall that programs would have to cover by sources other than third-party reimbursement.

It should be noted that the current study deliberately includes only private insurance and Medicaid funding, and thus excludes all other forms of funding. Although the estimates are thus computed under conservative funding conditions, this ensures the greatest degree of generalizability across settings and geographical locations. Site visit reports indicate that in addition to private insurance and Medicaid, programs often relied upon a patchwork of funding sources, including foundations, local government, other federal grants and cross-subsidies from the host agency. Clearly, with such additional sources of funds, the sustainable minimum number of patients to be screened would be lower, the range of screens for sustainability would be higher and higher levels of surplus may be possible.

Although the scope of the current study is limited to the United States, its findings have relevance to countries other than the United States. The methodological approach used in the current study can be generalized readily to screening, BI and RT programs in other applications, including other countries. Even in countries with single-payer, universal insurance, individual provider organizations must still decide how to allocate scarce health-care resources.

The study has at least two potential limitations. First, although the model incorporates key real-world features, it is not sufficiently sophisticated to account explicitly for certain aspects of providing SBIRT services, including heterogeneity in provider or patient characteristics; patient flow dynamics during the course of a given day, month or year; sampling error on the estimates used for parameter values; and patient no-shows, which can be costly to providers.

Secondly, the data used for parameter values were sometimes derived from a limited number of observations, and no data were available at the time of the study to conduct external validation (this limitation is shared by many simulation models). External validation compares predictions from the model to estimates that are not a direct product of the model. Because the model requires assumptions (e.g. the amount of quasi-fixed cost per provider), sensitivity analyses are important. Nevertheless, only a limited set of sensitivity analyses were completed. Among the parameters unexamined using such analyses was the prevalence of substance use, which drew from estimates for the general population, rather than a population seeking health care. Because this parameter was used to simulate the number of patients needing services, we speculate that any bias that would be introduced by using this estimate is to reduce the number of patients presenting for services.

The study findings suggest at least four avenues for future research. First, more refined data are needed to assess the time spent in the activities. For example, recording separately the time practitioners spend in non-productive activities is one necessary component towards obtaining data that may help improve system efficiency. Secondly, data are needed to assess any innovations in practice toward improving efficiency, such as computerized screening using patients inputting responses directly into a tablet device or using group rather than individual intervention and treatment approaches. Thirdly, the existing model would benefit from improved data on key parameters, such as the proportion of generalists to specialists, and data and estimates for validating outputs. Fourthly, future modeling approaches should incorporate more explicitly the dynamics of service provision and patient flow and introduce statistical uncertainty for model inputs or heterogeneity at both the provider and patient levels.

Declaration of Interests
None.

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APPENDIX A. VALUES AND SOURCES FOR ADDITIONAL MODEL PARAMETERS

Parameter	Values	Source
Prevalence		
Hazardous substance use in U.S. population	17.8%	[33]
SBIRT services		
Screening		
Sensitivity/specificity of prescreen instruments	0.82/0.79	[38]
Sensitivity/specificity of screen instruments	0.83/0.79	[30]
Average length of prescreening (minutes)	0.9	Study data
Costs		
Space costs (sq ft/year)	$35.49	[39]
Staff time		
Maximum service delivery time, generalist (FTE)	0.2	Assumed
Maximum service delivery time, specialist (FTE)	0.8	Assumed

[a] All observations for prescreens are from generalist practitioners in an emergency department setting. As a result, there is no between- group variation.

Note: This table supplements Table 1 in the manuscript.

APPENDIX B: OPERATIONALIZING CONSTRAINTS

Constraint 1: Revenue is greater than or equal to cost

The constraint in its simplest form is

$$R \geq C. \quad (1)$$

To operationalize (1), it is necessary to expand it to account for the complexities inherent in characterizing SBIRT costs. Because the goal is to minimize patients, express (1) in terms of the number of patients served. Reimbursement is equal to average reimbursement, $\bar{R}$, times patients serviced, n:

$$\bar{R}n \geq C \quad (1b)$$

Cost can be separated into its component parts: quasi-fixed cost, F; variable cost, $\bar{V}$; and the cost of practitioner idle time, I:

$$\bar{R}n \geq F + \bar{V}n + I \quad (1c)$$

Practitioner idle time is a function of the practitioner's total available service time, T; the average time it takes to serve one patient, t; and the number of patients served. Multiplying this result by their salary, w, yields the cost of practitioner idle time:

$$I = w(T - \bar{t}n) \quad (1d)$$

Average surplus, $\bar{S}$, is average reimbursement minus average variable cost:

$$\bar{S} = \bar{R} - \bar{V} \quad (1e)$$

Substituting (1d) and (1e) into (1c) and re-arranging yields the following:

$$(\bar{S} + \bar{t}w)n \geq F + Tw \quad (1f)$$

Steps 1b through 1f assumed that there was one kind of practitioner. This was expanded to two types of practitioners—generalists (subscript G) and specialists (subscript S)—and two types of patients—those screened by generalists (subscript 1) and those screened by specialists (subscript 2). Distinguishing between these practitioner and patient types gives 1g, below. This expression is used as the constraint in the solving algorithm for Question 1.

$$(\bar{S}_1 + \bar{t}_{1S}w_S)n_1 + (\bar{S}_2 + \bar{t}_{2S}w_S)n_2 \geq F + T_S w_S \quad (1g)$$

The expression for solving the surplus maximization in Question 2 is derived from (1g):

$$(\bar{S}_1+\bar{t}_{1S}w_S)n_1+ (\bar{S}_2+\bar{t}_{2S}w_S)n_2\text{-}F+T_S w_S \quad (1h)$$

Constraint 2: The number of patients screened by generalists is constrained by generalist and specialist availability

The second constraint is that the number of patients screened by generalists, n_1, is constrained by the available generalist time to screen and provide initial services (calculated by dividing the total available generalist time, T_G, by the amount of time it takes a generalist to serve an average patient screened by that generalist, t_{1G}) and the available specialist time to provide higher level services to the patient (calculated by dividing the total available specialist time, T_S, by the amount of time it takes a specialist to serve an average patient screened by a generalist, t_{1S}). Constraint 2 is as follows:

$$n_1 \leq \min\left(\frac{T_S}{t_{1S}}, \frac{T_G}{t_{1G}}\right) \quad (2)$$

Constraint 3: The number of patients screened by specialists is constrained by specialist availability for providing downstream services

The third constraint is that, because specialists must be available to provide higher level services to patients screened by generalists, the number of patients screened by specialists, n_2, is constrained by the amount of time specialists have to set aside to conduct activities such as follow-up BI, BT, and RT, and the amount of time a specialist must devote to the average patient that they screen themselves, t_{2S}. Constraint 3 is as follows:

$$n_2 \leq \frac{T_S\text{-}t_{1S}n_1}{t_{2S}} \qquad (3)$$

APPENDIX C. FINANCIALLY SUSTAINABLE RANGES OF ANNUAL NUMBER OF SCREENS FOR SBIRT PROGRAMS

Inpatient with Prescreen

Number of Specialists	Number of Generalists: 0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	2,852 to 2,995	3,147 to 3,931	3,583 to 4,867	4,020 to 5,803	4,457 to 6,739	4,894 to 7,675	5,331 to 7,999	5,768 to 7,999	6,205 to 7,999	6,642 to 7,999	7,079 to 7,999	7,516 to 7,999	7,953 to 7,999	—	—	—
2	5,704 to 5,990	5,923 to 6,926	6,293 to 7,862	6,730 to 8,798	7,167 to 9,734	7,604 to 10,670	8,041 to 11,606	8,478 to 12,542	8,915 to 13,478	9,352 to 14,414	9,789 to 15,350	10,225 to 15,998	10,662 to 15,998	11,099 to 15,998	11,536 to 15,998	11,973 to 15,998
3	8,555 to 8,985	8,775 to 9,921	9,003 to 10,857	9,440 to 11,793	9,877 to 12,729	10,314 to 13,665	10,750 to 14,601	11,187 to 15,537	11,624 to 16,473	12,061 to 17,409	12,498 to 18,345	12,935 to 19,281	13,372 to 20,217	13,809 to 21,153	14,246 to 22,089	14,683 to 23,025
4	11,407 to 11,980	11,627 to 12,917	11,846 to 13,853	12,149 to 14,789	12,586 to 15,725	13,023 to 16,661	13,460 to 17,597	13,897 to 18,533	14,334 to 19,469	14,771 to 20,405	15,208 to 21,341	15,645 to 22,277	16,082 to 23,213	16,519 to 24,149	16,956 to 25,085	17,392 to 26,021
5	14,259 to 14,976	14,478 to 15,912	14,698 to 16,848	14,917 to 17,784	15,296 to 18,720	15,733 to 19,656	16,170 to 20,592	16,607 to 21,528	17,044 to 22,464	17,480 to 23,400	17,917 to 24,336	18,354 to 25,272	18,791 to 26,208	19,228 to 27,144	19,665 to 28,080	20,102 to 29,016

Outpatient with Prescreen

Number of	Number of Generalists: 0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	3,087 to 4,789	3,324 to 6,272	3,562 to 7,754	3,799 to 9,236	4,037 to 10,407	4,274 to 10,407	4,511 to 10,407	4,749 to 10,407	5,105 to 10,407	5,486 to 10,407	5,867 to 10,407	6,248 to 10,407	6,630 to 10,407	7,011 to 10,407	7,392 to 10,407	7,773 to 10,407
2	6,174 to 9,579	6,411 to 11,061	6,649 to 12,544	6,886 to 14,026	7,123 to 15,508	7,361 to 16,991	7,598 to 18,473	7,836 to 19,955	8,073 to 20,814	8,310 to 20,814	8,548 to 20,814	8,785 to 20,814	9,023 to 20,814	9,260 to 20,814	9,497 to 20,814	9,829 to 20,814

3	9,261 to 14,368	9,498 to 15,851	9,736 to 17,333	9,973 to 18,815	10,210 to 20,298	10,448 to 21,780	10,685 to 23,262	10,923 to 24,745	11,160 to 26,227	11,397 to 27,709	11,635 to 29,192	11,872 to 30,674	12,110 to 31,221	12,347 to 31,221	12,584 to 31,221	12,822 to 31,221
4	12,348 to 19,158	12,585 to 20,640	12,823 to 22,122	13,060 to 23,605	13,297 to 25,087	13,535 to 26,569	13,772 to 28,052	14,010 to 29,534	14,247 to 31,017	14,484 to 32,499	14,722 to 33,981	14,959 to 35,464	15,196 to 36,946	15,434 to 38,428	15,671 to 39,911	15,909 to 41,393
5	15,435 to 23,947	15,672 to 25,429	15,909 to 26,912	16,147 to 28,394	16,384 to 29,877	16,622 to 31,359	16,859 to 32,841	17,096 to 34,324	17,334 to 35,806	17,571 to 37,288	17,809 to 38,771	18,046 to 40,253	18,283 to 41,735	18,521 to 43,218	18,758 to 44,700	18,996 to 46,182

ED with Prescreen

	Number of Generalists															
Number of Specialists	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	3,156 to 4,031	3,393 to 5,093	3,629 to 6,154	3,866 to 7,216	4,157 to 8,278	4,575 to 8,436	4,994 to 8,436	5,412 to 8,436	5,830 to 8,436	6,248 to 8,436	6,666 to 8,436	7,084 to 8,436	7,503 to 8,436	7,921 to 8,436	8,339 to 8,436	—
2	6,312 to 8,062	6,549 to 9,124	6,786 to 10,186	7,022 to 11,247	7,259 to 12,309	7,495 to 13,370	7,732 to 14,432	7,968 to 15,494	8,314 to 16,555	8,733 to 16,872	9,151 to 16,872	9,569 to 16,872	9,987 to 16,872	10,405 to 16,872	10,823 to 16,872	11,242 to 16,872
3	9,469 to 12,093	9,705 to 13,155	9,942 to 14,217	10,178 to 15,278	10,415 to 16,340	10,651 to 17,402	10,888 to 18,463	11,125 to 19,525	11,361 to 20,586	11,598 to 21,648	11,834 to 22,710	12,071 to 23,771	12,472 to 24,833	12,890 to 25,308	13,308 to 25,308	13,726 to 25,308
4	12,625 to 16,125	12,861 to 17,186	13,098 to 18,248	13,335 to 19,309	13,571 to 20,371	13,808 to 21,433	14,044 to 22,494	14,281 to 23,556	14,517 to 24,617	14,754 to 25,679	14,991 to 26,741	15,227 to 27,802	15,464 to 28,864	15,700 to 29,926	15,937 to 30,987	16,211 to 32,049
5	15,781 to 20,156	16,018 to 21,217	16,254 to 22,279	16,491 to 23,341	16,727 to 24,402	16,964 to 25,464	17,200 to 26,525	17,437 to 27,587	17,674 to 28,649	17,910 to 29,710	18,147 to 30,772	18,383 to 31,833	18,620 to 32,895	18,856 to 33,957	19,093 to 35,018	19,330 to 36,080

Note: Values refer to full screens; the ratio of prescreens to full screens is approximately 3 to 1.