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How to Identify Students for School-based Depression Intervention: Can School Record Review Be Substituted for Universal Depression Screening?

Elena S. Kuo, Ph.D., MPH,
Research Associate, Group Health Research Institute

Ann Vander Stoep, Ph.D. [Associate Professor],
University of Washington, Department of Psychiatry and Behavioral Sciences, Department of Epidemiology

Jerald R. Herting, Ph.D. [Professor],
University of Washington, Department of Sociology and Department of Psychosocial and Community Health

Katherine Grupp, PhD, ARNP [Private Practitioner], and
Seattle, WA

Elizabeth McCauley, Ph.D. [Professor]
Department of Psychiatry and Behavioral Sciences, University of Washington, Division of Child and Adolescent Psychiatry, Seattle Children's Hospital

Abstract

Problem—Early identification and intervention is critical for reducing the adverse effects of depression on academic and occupational performance. Cost-effective approaches are needed for identifying adolescents at high depression risk. This study evaluated the utility of school record review versus universal school-based depression screening for determining eligibility for an indicated depression intervention program implemented in the middle school setting.

Methods—Algorithms derived from grades, attendance, suspensions, and basic demographic information were evaluated with regard to their ability to predict students' depression screening scores.

Findings—The school information-based algorithms proved poor proxies for individual students' depression screening results. However, school records showed promise for identifying low, medium, and high yield subgroups on the basis of which efficient screening targeting decisions could be made.

Conclusions—Study results will help to guide school nurses who coordinate indicated depression intervention programs in school settings as they evaluate options of approaches for determining which students are eligible for participation.

A key objective of Healthy People 2020 is to increase “the proportion of children with mental health problems who receive treatment (4-17 year-olds)” (U.S. Department of Health and Human Services, 2012). Adolescent depression constitutes a major public health problem; as many as 20% of U.S. youth experience an episode of major depression by age 18, and as many as 65% of adolescents report depressive symptoms (Kessler et al., 1994;

Lewinsohn, Hops, Roberts, Seeley, & Andrews, 1993). Depressive episodes in adolescents last an average of 7-9 months, and 5-year recurrence rates approach 70% (Lewinsohn, Roberts, Rohde, Gotlib, & Hops, 1994; McCauley et al., 1993; Rao et al., 1995). Depression is associated with adverse outcomes, including poor school performance (Glieb & Pine, 2002; Rao et al., 1995; Vander Stoep et al., 2000), which is correlated with the duration of depressive symptoms (Kovacs & Goldston, 1991). Adults who experienced depression as adolescents are at increased risk for recurrent depressive disorders, substance use disorders, impairment in vocational and social roles, chronic health problems and suicide (Belsher & Costello, 1988; Garber & McCauley, 2002; Lewinsohn, Solomon, Seeley, & Zeiss, 2000; Mental Health Commission, 2003; Nolen-Hoeksema, Girgus, & Seligman, 1992; Rohde, Lewinsohn, & Seeley, 1994; Sharp & Lipsky, 2002). These outcomes result in significant social and economic costs; the World Health Organization has cited depression as the leading cause of disability worldwide and as the fourth leading contributor to the global burden of disease (World Health Organization, 1996; World Health Organization, 2004). Given these major ramifications, universal depression screening for adolescents has been recommended, but only when systems are in place to ensure that follow-up evaluation and intervention are accessible to those who screen positive (Agency for Healthcare Research and Quality, 2009).

According to the National Association of School Nurses (NASN), mental and emotional disorders are chronic health conditions that are within the scope of school nurses' practice (National Association of School Nurses, 2012). Nurses in school settings are ideally situated to identify children and adolescents who are in need of services to treat or prevent mental health problems including depression. School nurses have established four criteria to consider when deciding whether to conduct screening in the school setting: affordability, ease of administration, the ability of the instrument to be rapidly scored, reliability and validity (Carnevale, 2011). These criteria suggest the need for cost-effective screening approaches, which for identifying students at risk for depression, translates into a screen with adequate sensitivity and specificity balanced with containment of costs.

Once risk is identified, intervention with adolescents experiencing early signs of depression can significantly reduce depressive symptoms and incidence of depression (Clarke et al., 2001; Gillham, Reivich, Jaycox, & Seligman, 1995; Jaycox, Reivich, Gillham, & Seligman, 1994). For adolescents already experiencing clinical depression, early identification and appropriate intervention can result in relief from symptoms, a lower risk of recurrence, and improvement in outcomes such as academic performance (Allgood-Merten, Lewinsohn, & Hops, 1990; Brent et al., 1997; Garber, 2006; Garber & McCauley, 2002; Kahn, Kehle, Jenson, & Clark, 1990; Kazdin & Weisz, 1998; Lewinsohn & Clark, 1999; Schochet et al., 2001). Longitudinal research also indicates that treatment of adolescent depression significantly reduces risk of depression during adulthood (Feehan, McGee, & Stanton, 1993; Harrington, Rutter, & Fombonne, 1996). The potential benefits of minimizing long-term adverse effects underscore the necessity for early identification and intervention.

School-based implementation of depression-focused interventions has gained in popularity and acceptability over the last 20 years, in part due to increased recognition of the potential benefits and increased federal support (Paternite, 2005). The school setting enables programs to serve youth with a wide range of social, cultural, and economic backgrounds, and extends the reach of effective interventions to youth who may otherwise have limited access (Adelman & Taylor, 1991; Flaherty, Weist, & Warner, 1996; Mental Health Commission, 2003).

A variety of school-based depression prevention models have been implemented to date, including universal, selected, and indicated interventions. Universal programs, such as Signs

of Suicide that provides classroom-based education and screening, enroll all students regardless of risk (Aseltine & DeMartino, 2004). The Developmental Pathways Program provides universal depression screening followed by clinical evaluation and referral for those who screen positive (Vander Stoep et al., 2005). Other interventions are geared toward selected groups of students at risk for depression; for example due to a recent parental divorce (Pedro-Carroll & Cowen, 1985) or due to a parental history of clinical depression (Beardslee & Wheelock, 1994; Clarke et al., 2001). Indicated interventions such as the Penn Prevention Programs and the Clarke Programs enroll adolescents with subclinical symptoms of depression (Clarke et al., 2001; Gillham, Reivich, Jaycox, & Seligman, 1995; Jaycox, Reivich, Gillham, & Seligman, 1994), while other indicated programs enroll adolescents who are experiencing clinical depressive disorder (Seligman, Schluman, DeRubeis, & Hollon, 1999; Shochet et al., 2001).

A meta-analytic review conducted in 2006 determined that indicated depression interventions tend to be more effective than universal ones (Horowitz & Garber, 2006). In addition, programs that address depression are less costly when implemented within targeted high risk subgroups, rather than universally (Hargreaves, Shumway, Hu, & Cuffel, 1998). Therefore, a shift is occurring toward implementation of indicated intervention models for prevention of depression.

Identifying eligible students is a key component of indicated intervention programs; however very little research has been devoted to determining optimal methods. Teacher nomination, parent nomination, and direct depression screening of students are three methods that have been employed to determine eligibility. Implementation of teacher or parent nomination meets the criterion of minimal cost. Teacher nomination strategies are based on the assumption that adults who are familiar with individual students within the school setting can accurately identify signs of depression and nominate students at risk (Auger, 2004; Lane, 2003). However, one study found that teachers, even with training, nominated fewer than half of students found to be clinically depressed through screening and clinical evaluation (Moore et al., 2007). Another study reported teacher nomination to have a sensitivity of less than 35% for identifying students with internalizing disorders (Dwyer, Nicholson, & Battistutta, 2006). Regarding parent nomination, research indicates that parents typically underreport depressive symptoms compared to adolescent self-report (Edelbrock, Costello, Dulcan, Conover, & Kala, 1986; Logan & King, 2001); in general, parent report is considered less accurate than adolescent self-report (Clarke et al., 2001; Logan & King, 2001).

Student self-report is an identification method employed by several programs, involving administering screening questionnaires and/or interviewing students prior to selection (Flaherty, Weist, & Warner, 1996). Although self-report depression screening has been shown to be more accurate than others' reports (Garber & McCauley, 2002; Horowitz & Garber, 2006); it is more costly, time-consuming, and potentially exclusionary if parental permission is required for participation.

Given low accuracy of others' reports of adolescent depression status and high costs of student depression screening, the question arises as to whether information contained in school records might be employed as a less costly method for identifying students at risk for depression and other emotional problems. As stated previously, prior research has demonstrated a strong association between mental health status and school performance (Glieb & Pine, 2002; Mental Health Commission, 2003; Nolen-Hoeksema et al., 1992; Vander Stoep et al., 2000). However, little research has been conducted to investigate how well school record data perform compared to student screening for identifying youth at risk for depression. The National Longitudinal Study of Adolescent Health, conducted with high

school students, was one of the few studies to explore this question. Researchers reported a significant difference in depression scores for youth with academic and behavioral school problems from those with fewer school problems. Over 40% of the problem-vulnerable 9th graders were in the highest quartile of depression scores (Bearman, Jones, & Urdry, 2003). These findings suggest that information from a review of school records may have high positive predictive value, but leave in question the issue of sensitivity with respect to identification of depressed youth.

The current study builds on these findings by evaluating the utility of school record review versus depression screening for determining eligibility for an indicated depression preventive intervention program. Self-report depression screens are compared to an algorithm derived from grades, attendance, suspensions, and basic demographic information available from school records. This paper examines 1) the sensitivity and specificity of a school record data-based algorithm compared to screening scores to determine whether school records might be a good alternative to universal screening, and 2) differences in the sensitivity and specificity of school record data within specific high and low risk subgroups to identify subgroups of students toward which screening efforts might be targeted. Results will help inform nurses who are charged with coordinating indicated depression programs in school settings to select accurate and efficient methods for identifying students for intervention.

Method

Data for this research are derived from Stage 1 data from the High School Transition Study (HSTS), a trial of a preventive intervention program for middle school students at risk for depression. HSTS is carried out in two stages. Stage 1 is the identification phase, when universal classroom-based screening of 8th grade students is conducted to select students exhibiting early signs of depression. Stage 2 is the intervention phase, conducted among students who screen positive in Stage 1. The intervention includes small group classes for 8th grade students, individual booster sessions during 9th grade, and in-home parent sessions during both 8th and 9th grades. A more detailed description of HSTS methodology can be found elsewhere (McCauley, Vander Stoep, & Pelton, 2004). The data for this study were derived from the first three years of HSTS recruitment.

Participants and Procedure

The study was conducted in Seattle, Washington. A total of 46,730 students, or 67.8% of school-aged children residing in Seattle, were enrolled in the Seattle Public School District during the 2003-2004 academic year. Of the 10,198 middle school students enrolled in the district's 10 middle schools (grades 6-8), 23.1% were African American, 22.9% were Asian, 10.4% were Hispanic, 2.7% were Native American, and 40.9% were Caucasian. Thirty-five percent of middle school students received free or reduced-cost lunches, and 23.4% spoke a language at home other than English. Six of the 10 middle schools in the district implemented the HSTS program. The students enrolled in participating schools during 2002-2005 school years had an ethnic and racial distribution similar to that of all enrolled students in the district.

Procedures were approved by the University of Washington Human Subjects Review Board and the Seattle Public Schools Office of Research, Evaluation and Assessment. Recruitment materials, including a letter from the school principal, an information sheet, and a consent form were mailed to parent/guardians of 8th grade students. Students completed the screening questionnaire only if a parent/guardian gave written consent, the student provided written assent, and the student was able to understand spoken English at a third grade level. The questionnaire was administered in a classroom setting during one 50-minute period.

Eligibility for intervention was based in part on scoring above a designated threshold on the depression screening questionnaire.

Measures

Students were screened for signs of depression using the Mood and Feelings Questionnaire (MFQ) (Angold & Costello, 1987). The MFQ was designed as a screening tool for depression in child psychiatric epidemiological studies. Items are statements derived from the DSM diagnostic criteria for major depressive disorder and dysthymia (Costello & Angold, 1988). The 33-item self-report questionnaire can be administered to youth aged 8-18 years. High test-retest reliability and good convergent validity with a diagnosis of depression have been demonstrated (Costello & Angold, 1988; Pellegrino, Sing, & Carmanico, 1999; Sund, Larsson, & Wichstrom, 2001). For this study, three suicide-related items were removed due to their sensitive nature, the program staff's inability to provide sufficient privacy for questionnaire administration, and the inadequate resources to evaluate the large number of youth who warrant follow up for endorsing items such as "I thought of death or dying" but are actually "false positives" for suicide or depression risk (Vander Stoep, McCauley, Flynn, and Stone, 2009).

On the questionnaire, students were asked to report how true each item was for them in the past two weeks on a 3-point Likert scale; "not true," "somewhat or sometimes true," or "very true or often true". Questionnaires were electronically scanned, and total depression score was calculated. Incomplete questionnaires were retained for analysis if at least 75% items were answered. Missing items were imputed as the average value of answered items. Students were eligible if they scored at or above 15 on the MFQ, corresponding to 0.5 SD above the sample mean. This cut-off was selected to target students reporting early signs of depression, as well as those students who would be considered clinically depressed.

At the time of screening, demographic data including gender, special education status, English Language Learner status, and home language were obtained from the school district for all enrolled students. At each school year's end, GPA for the 8th grade year, % days attended, and number of suspensions was provided for all participating students by Seattle Public Schools.

Analyses

Two analytic approaches were employed to examine how accurately a school record information algorithm predicted eligibility for program participation, as determined by the depression screening results. First, multiple logistic regression was conducted using SPSS Version 13.0 (SPSS Inc., 2004). Logistic regression is widely used for creating an algorithm for predicting a dichotomous outcome. The following school and demographic information was examined as potential predictors: first semester 8th grade GPA (continuous), percent of days attended out of days enrolled in past year (continuous), number of school suspensions in the past year (numerical), language spoken in the home (categorical: 54 languages), race (categorical: African American, Asian, Native American, Caucasian), Hispanic ethnicity (categorical: yes, no), enrollment in special education (categorical: yes, no), in an English Language Learner Program (categorical: yes, no) and gender (categorical: male or female). To determine the optimal cutoff, predicted probabilities of eligibility based on the regression equation were plotted on a Receiver Operating Curve (ROC).

The second analytic approach was classification and regression tree analysis using CART software (Salford Systems, 1999) to determine what combination of school record variables best predicted program eligibility as determined by the depression screening results. Regression tree analysis (Breiman, Friedman, Olshen, & Stone, 1984) is a technique

typically used to generate clinical decision rules. For example, in one study CART was utilized to select the optimal set of demographic and diagnostic variables to predict whether a patient's lung fluid was likely to be systemic versus inflammatory, thereby informing the treatment approach (Esquerda et al., 2007).

This study created a regression tree chart that “branched” by using an iterative process that selected variables one at a time to divide students into two subgroups, or nodes, that were as mutually exclusive or “pure” as possible with regard to eligibility for intervention. CART first dichotomized the sample on the basis of a single predictor at the point where the sorting into eligible and ineligible groups was most distinctive. A continuous variable would be cut in two at a point along the distribution of values; for example GPA might be cut in two subgroups of ≤ 2.4 and >2.4 or ≤ 2.8 and >2.8 , etc. A categorical variable such as home language would be evaluated in various two subgroup combinations of languages. After each split, CART searched all remaining variables and selected the next best predictor variable and its optimal cut-off point. For this study, the regression tree model was set to split only if there were at least 50 students left in a subgroup and to only allow up to 10 splits. The splitting criterion was the Gini Index measure of impurity, and the tree was validated using 10-fold cross validation to prune to the optimal tree.

The regression tree model fitted for the current study utilized the same school record data variables used for the logistic regression analysis with three exceptions: sex, race, and ethnicity. With logistic regression, decisions are made after considering several factors, but with regression tree analysis, a decision might be made based on one factor. For example, a logistic regression analysis might indicate that a white female, $GPA > 3.0$, fewer than 5% days absent, no suspensions has a 5% probability of being eligible, and an African American female with the same characteristics has a 40% probability of being eligible, and the researcher would choose a probability cutoff on which to base eligibility. However, a regression tree analysis might produce a tree where an African American child and a Caucasian child with otherwise identical predictors might be eligible or ineligible solely based on race. It would be unethical to exclude someone from intervention on the basis of sex, race, or ethnicity. Because sex is known to modify the effects of potential predictor variables on depression, the sample was split first by sex, to create a regression tree with two sex-specific branches. Race and ethnicity were excluded from the regression tree analysis, but retained in the logistic regression analysis.

Results

Of the 3,320 8th grade students enrolled in participating schools from 2002-2005, a total of 2,006 students were screened (60.5%). Of non-participants, 302 parents declined (9.1%), 975 parents did not return a permission form (29.4%), and 37 students declined (1.1%). Of the 2,006 screened students, 627 (31.3%) were eligible for intervention based on MFQ total scores. Chi square tests for categorical variables and t-tests for continuous variables indicated that eligible and ineligible screened students were significantly different at the $p = .05$ level with regard to all demographic and school record variables. Eligible students had lower GPAs, more days absent, more disciplinary actions, were more often female, more likely to be in a special education program or in an English Language Learner (ELL) program, more often belonged to a non-Caucasian race, and more often spoke a language other than English in the home (see Table 1).

Logistic Regression Analysis

Forward step-wise logistic regression was conducted utilizing eligibility for HSTS intervention as the dichotomous outcome variable of interest and gender, race, ethnicity, special education status, ELL status, home language, 8th grade GPA, % days attended, and

number of suspensions as potential predictor variables. The α levels were set at $p=.05$ for inclusion and $p=.10$ for exclusion. The resulting equation contained 8th grade GPA, language spoken in the home, and gender as the sole significant predictors of eligibility (adjusted $R^2=.70$ in the final model). The final model was as follows:

$$\text{Logit (HSTS eligibility)} = 1.73 - .94 (\text{male}) - .71 (8^{\text{th}} \text{GPA}) + .39 (\text{NonEng home lang})$$

Adding interaction or squared terms did not appreciably affect the model. The percent of students correctly classified at the predicted probability cutoff of $>.50$ was 70.8. The sensitivity (percent of eligible students predicted to be eligible) at this cutoff value was 22.8%, meaning that of 627 eligible students, 143 would be correctly identified, and 484 students would be false negatives. The specificity (percentage of ineligible students predicted to be ineligible) was 93.1%, meaning that the formula would correctly identify 1,284 of 1,379 ineligible students as ineligible, and 95 students would be false positives.

Plotting predicted probabilities of meeting eligibility criteria using the prediction equation in a ROC produced an area under the curve (AUC) of .69 (95% CI .66-.72). An AUC=.50 is indicative of a test with no discriminative value for predicting an outcome, and AUC=1.0 is indicative of a test with perfect discrimination. This equation would correctly discriminate between an eligible and an ineligible student in 69% of cases (see Figure 1).

Regression Tree Analysis

CART generated the tree shown in Figure 2. Each node depicts the number of ineligible (Class=0) and eligible (Class=1) students included in the subgroup. To evaluate diagnostic performance, each terminal node was designated as predicting either eligible or ineligible students, depending on which designation comprised $>50\%$ of the students in that node. Results indicated that 300 of 627 eligible students were correctly identified, for an overall sensitivity of 47.8%, with 327 false negatives. Of the 1,379 ineligible students, 1,220 were correctly classified, for a specificity of 87.0%, with 179 false positives. Of the 1,547 students predicted to screen negative, 1,220 did so, for a negative predictive value negative of 78.9%, and 300 of 459 students predicted to screen positive did so, for a positive predictive value of 65.4% overall.

Within the final subgroups, represented by the terminal nodes in Figure 1, predictive values varied greatly from the overall predictive value of the model. For example, Terminal Node 3 had a predictive value of 96.9% for *ineligible* students, as 186 of 192 students in this subgroup were ineligible for the intervention. Terminal Node 2 had a predictive value of 64.3% for *eligible* students, as 99 of 154 students were eligible for intervention. Others such as Terminal Node 7 had almost equal numbers of eligible and ineligible students; therefore membership in this subgroup held little predictive value with regard to eligibility. The diagnostic performance for each terminal node is presented in Table 2.

Discussion

Study results showed that for middle school students, school record information was a poor proxy for a depression screening score in determining eligibility for a depression-focused intervention. School record information might, however, be used profitably to organize and target screening efforts more efficiently by identifying the characteristics of subgroups of students who would have very high yields, very low yields, and mixed yields of high scorers on a depression screening scale. These results have implications for school nurses who are charged with implementing such interventions in middle-school settings, including determining students' eligibility.

In general, study results were consistent with prior research findings that show a strong association between depression scale scores and poor school performance. In our study, students who were eligible and ineligible for intervention based on depression screening results differed significantly on every school indicator, including GPA, attendance, and disciplinary actions. Despite strong associations, neither of our analytic approaches created a school data-based algorithm with good sensitivity or positive predictive value. The logistic regression analysis yielded a positive predictive value of only 71%, and the regression tree analysis yielded a slightly lower positive predictive value of 65.4%. A false positive rate of over 20% may be unacceptably high when determining eligibility for any resource-heavy intervention. Application of the logistic regression algorithm resulted in a sensitivity under 25%, and sensitivity using the regression tree was less than 50%. Missing 50-75% of students showing early signs of depression may be unacceptably high for a health problem with such significant adverse academic and other consequences.

School data may be useful insofar as it could be used to identify groups of students to whom the school nurse could target screening efforts. In this study, CART identified some subgroups with a very high predictive value for identifying students who were *ineligible*. Terminal Node 3, for example, was comprised of students who were male, had parents who spoke English/European Language in the home, and who had a GPA >3.5. A very high proportion (186/192) of students with this combination of characteristics was ineligible for intervention. Exempting from screening subgroups whose members are unlikely to be eligible would free more resources to invest in screening other students with a greater likelihood of program eligibility. Even if schools prefer universal screening, nurses could guide school districts in using this knowledge to target more aggressive recruitment efforts such as phone calls to parents and multiple classroom visits toward groups of students with a higher likelihood of being eligible.

CART also identified subgroups with a mix of eligible and ineligible students, with a corresponding low predictive value. In this study, 87.7% of students were in subgroups with less than 80% predictive value for either program eligibility or ineligibility. A school could target screening towards some of these subgroups if the absolute number of eligible students, and thus the potential yield, were large. For example, screening only students from Node 4 and Terminal Node 8 equates to screening 1,168 students, only 58.2% of the total number of students screened. Targeting screening to only these two selected subgroups would lead to considerable cost savings while still identifying 325 eligible students. On the other hand, 302 eligible students falling into other nodes would be excluded from intervention. Nurses may not want to implement a screening program that excludes substantial numbers of depressed students. This issue could be addressed in some cases by screening students from *all* terminal nodes containing several eligible individuals. However, the pool of students needing screening would remain large, and cost or efficiency would not be appreciably affected.

In our CART analysis no subgroups were identified that had high predictive value for identifying students who met intervention eligibility criteria. Hypothetically, if such a subgroup were identified, members could be recruited directly into the intervention program without screening.

A review of school records to identify subgroups to whom screening efforts could be targeted can be accomplished quickly and would cost less than \$0.25 per enrolled student. In comparison, implementation of universal depression screening costs approximately \$7 per enrolled student (Kuo, Vander Stoep, Kernic, & McCauley, 2009) and requires multiple staff days to recruit students, administer the screen, and analyze responses, with time involvement increasing in proportion to the number of screened students. Depending upon

the prevalence of positive screens in the school, costs increase to \$8.88-\$13.64/student when immediate follow-up is implemented with students who have clinically elevated scores. Given the expense and time involved in screening and the potential for active consent to result in systematic exclusion of members of the desired population (Chartier et al., 2008), alternative methods would be preferable. However, in this study neither the logistic nor regression tree analyses were able to accurately identify depression-vulnerable students based on school record information. Therefore this less costly approach showed little promise for replacing depression screening.

A number of other issues besides accuracy and cost of the screen must be addressed to enable successful implementation of school-based mental health interventions. Other considerations include awareness by members of the school community: administrators, teaching and support staff, parents, and students of the importance of positive mental health for academic success. It is critical that channels of communication between the school nurse, school administration, the intervention program personnel, parents, teachers, and students be open and used effectively to inform the community about the goals and procedures of the intervention program and to address questions that arise. For example, key communications to parents may include: informing parents about the school-based intervention, obtaining parental permission to recruit students, informing parents about their child's eligibility for participation and details of what participation entails, obtaining permission to access academic records, sending reports of student progress in the intervention, and gathering parents' perspectives on program benefit. During intervention implementation, the student will devote time to learning about the program, giving assent to participate, being assessed for eligibility, taking part in the intervention, and providing perspectives on personal progress or satisfaction with the program. An important consideration is to minimize the disruption of students' academic activities, such that the benefits of participation in the intervention outweigh the risks of falling behind in school progress. Selecting an accurate, low cost, high yield means of identifying students whom the program is designed to benefit is one important factor in the benefit/risk equation.

This study had several limitations. One such limitation that may have affected the validity of study findings was the low screening participation rate (65%). The school district provided de-identified school records for unscreened students enabling a secondary analysis of characteristics of nonparticipants. Screened and non-screened students were significantly different on several factors that are associated with depression status, including gender, special education status, GPA, and number of suspensions (McCauley et al., 2004). Systematic exclusion of selected subgroups of enrolled students may have affected the regression tree results and compromised generalizability. As school-based emotional health screening gains in acceptability, the norm for requiring parental permission may shift from active (opt-in) to passive (opt-out) which will result in higher levels of participation (Chartier et al. 2008; Eaton, Lowry, Brener, Grunbaum, & Kann, 2004; Pokorny, Jason, Schoeny, Townsend, & Curie, 2001).

Another limitation was the small number of potential school record data variables available for analysis. Prior research indicates that having failed an earlier grade, a significant drop in GPA, and long-term attendance problems are predictive of school drop-out and emotional problems (Cairns, Cairns, & Neckerman, 1989; Eggert & Herting, 1993; Heyne, King, Tonge, & Cooper, 2001; Lever et al., 2004). Incorporating historical academic variables could improve predictive power, as could additional current school record information, such as free and reduced lunch status or standardized test performance. School districts with richer sets of potential predictors may have the ability to create a more accurate depression risk prediction model than was possible in this analysis.

This study was conducted with middle school students. Results may not be generalizable to elementary or high school students, given that both depression incidence and expression vary across developmental stages (Birmaher et al., 1996; Messina & Tiefemann, 2006). For example, work by Thompson and colleagues suggests that the association between depression scores and GPA and absences in high school students may be stronger than the association observed in this middle school population (E. Thompson, personal communication, 2001).

School record data may have more utility to identify other mental health conditions besides depression. For example, a secondary regression tree analysis using school record data to identify adolescents with high levels of externalizing problems found that school records had 35% sensitivity and 97% specificity overall, but sensitivity in several subgroups approached 100%. Therefore, future research to explore the utility of school record review for identifying emotional health problems other than depression may prove fruitful.

Conclusion

The school nurse can play a pivotal role in advancing prevention and early intervention for students with mental health problems. Early intervention is critical for reducing the academic, social, and economic burden of depression; therefore continued efforts to develop and use cost-effective approaches for identifying at-risk adolescents are needed. This study showed that school record data were a poor proxy for universal depression screening in determining which middle school students had early signs of depression. School record data may, on the other hand, help the school nurse in targeting subgroups of students for more intensive recruitment. The results of this study can guide school nurses who implement targeted depression interventions in implementing recruitment strategies that best suit the unique population, needs and budget of the school and community.

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Figure 1.
ROC Curve Showing Sensitivity and Specificity of Predicted Probability of Program Eligibility Using Logistic Regression Equation.

Figure 2.
Regression Tree for School Record Information.

Table 1

Demographic and School Record Characteristics of Eligible versus Ineligible Screened Students

	Characteristics	Eligible		Ineligible		Significance
		N	%	N	%	P*
Gender	Male	221	35.2	711	51.6	<.001
	Female	406	64.8	668	48.4	
Special Education	In the program	66	12.5	98	6.7	<.001
Status	Not in the program	462	87.5	1336	93.3	
ESL Status	In the program	59	9.5	73	5.3	.001
	Not in the program	565	90.5	1301	94.7	
Race	African American	103	16.4	165	12.0	.005
	Asian	149	23.8	281	20.4	
	Native American	116	18.5	298	21.6	
	Caucasian	259	41.3	635	46.0	
Ethnicity	Hispanic	103	16.4	168	12.2	.012
	Not Hispanic	524	83.4	1211	87.8	
Home Lang	English	467	74.5	1109	80.4	.002
	European (not Spanish)	6	1.0	23	1.7	
	Other	154	24.6	47	17.9	
		Mean	SD	Mean	SD	
	GPA	2.85	0.88	3.25	0.75	<.001
	% days attended	91.3	7.9	94.5%	5.3	.001
	# of suspensions	0.29	0.85	0.15	0.54	<.001

* Chi Square test for categorical variables and T test for continuous variables

Table 2

Diagnostic Performance of Different Terminal Nodes from Regression Tree Analysis

Node	N	Group Classification	Prediction Direction	Predictive Value	Misclassify Rate
1	407	Male, Home Lang =English/European GPA >3.5, Absences <8%	Ineligible	84.5	15.5
2	154	Male, Home Lang =English/European GPA >3.5, Absences >8%	Eligible	64.3	35.7
3	192	Male, Home Lang =English/European GPA>3.5	Ineligible	96.9	3.1
4	70	Male, Home Lang =Spanish/Other GPA <2.8	Ineligible	57.1	42.9
5	24	Male, Home Lang =Spanish/Other GPA>2.8, GPA <3.2	Ineligible	100	0
6	85	Male, Home Lang =Spanish/Other GPA>3.2	Ineligible	72.9	7.1
7	245	Female, Home Lang =English/European GPA <3.0	Eligible	58.0	42.0
8	607	Female, Home Lang =English/European GPA >3.0	Ineligible	73.1	26.9
9	80	Female, Home Lang =Spanish/Other ELL or SPED	Eligible	73.8	26.2
10	113	Female, Home Lang =Spanish/Other Regular classes, Absences>3%	Ineligible	64.6	35.4
11	29	Female, Home Lang =Spanish/Other Regular classes, Absences <3%	Ineligible	93.1	6.9