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Usefulness of Clinical Predictors for TB Isolation

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Respiratory isolation places an enormous financial burden on hospitals that care for a substantial number of patients with tuberculosis (TB) and, in particular, public hospitals, which care for most of these patients in the United States.

Grady Memorial Hospital, a public hospital in Atlanta, cares for approximately 200 patients with active TB each year. An expanded respiratory isolation policy was implemented recently that resulted in a dramatic reduction in exposure episodes (from 4.4 to 0.6 episodes per month) and an accompanying reduction in tuberculin skin-test conversion rates in healthcare workers. The expanded policy made respiratory isolation mandatory for all patients with active TB, with TB in the differential diagnosis, or with acid-fast bacilli (AFB) sputum smears and cultures ordered, as well as for all HIV-infected patients with abnormal chest radiographs until three sputum smears negative for AFB were obtained. The expanded respiratory isolation policy resulted in appropriate isolation of more than 95% of patients with TB on admission, but also resulted in an eightfold overuse of isolation rooms. Researchers at Grady Memorial sought to modify this policy to reduce unnecessary admission to isolation by evaluating the usefulness of clinical information available to admitting physicians for predicting active TB. Clinical findings in 295 patients admitted to respiratory isolation during a 3-month period were evaluated for their usefulness in determining which patients had TB. Multivariate analysis identified five predictive variables, including chest radiograph with upper lobe infiltrate or cavity, self-reported positive tuberculin skin test, and self-reported isoniazid preventive therapy. Using these variables to develop a hypothetical policy to determine which patients required isolation would have decreased the number of isolated non-TB patients during the study period from 253 to 95, but it would have missed 8 of the 42 patients with TB.

The authors note that the strongest predictors of active TB among all patients admitted to respiratory isolation was chest radiographic findings of an upper lobe infiltrate or pulmonary cavity. However, stratifying by HIV serostatus eliminated this association for patients who were HIV seropositive, findings consistent with numerous other reports.

The authors conclude that the low sensitivity of the hypothetical policy made it an unacceptable alternative for their hospital. They suggest that further work is needed to identify clinical predictors that would decrease overuse of isolation beds while maintaining satisfactory sensitivity for patients with TB.

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