Early Identification of Long-Term Poor Adherence in Ambulatory Patients

TO THE EDITOR: Poor adherence leads to poor disease control and increased costs.[1] Early identification of patients at risk for long-term poor adherence is therefore important. We investigated whether early identification of patients at risk for long-term poor adherence is possible in a community pharmacy setting by performing a case–control study that consisted of a group of patients receiving drug therapy for at least one year.

Methods. The medication possession ratio (MPR), calculated by dividing cumulative days of drug supply by total number of days in the interval in which the drug was obtained, was used as a proxy for nonadherence.[2] Cases were patients with an MPR of 80% or less in the year following the sixth dispensing of a drug; controls were all other patients within the study population. We recalculated MPR one year after the sixth dispensing to ensure independence of the data for the first 5 refills from the one year adherence data. The main determinant was MPR at fills 2 (average 43 days), 3 (103), 4 (161), and 5 (222). Other predictors were patient age, number of prescriptions in one year, and total number of drugs used between fills 1 and 5. We did not include number of daily doses as a possible predictor due to changes in dosing frequencies over time. A multivariate logistic regression model was used to assign a risk score, with the regression coefficient multiplied by 10 and rounded to the nearest integer as the score for each predictor variable. Total risk scores (sum of all individual predictors) were calculated for each patient.

Results. From 3845 patients who received new prescriptions during the study period, we identified 606 (16%) cases and 3239 controls. Average age of patients was 67.1 years, and 41.7% were male. Average number of different medications being taken was 11.7 per patient between fills 1 and 6. Overall nonadherence in our study was low (16%) compared with the percentage in other studies (as high as 50%[1]), probably because we included only patients who were persistent for over one year, thus excluding initial nonadherence that is frequently present in patients who discontinue drug therapy prematurely.[3]

Table 1 shows adjusted regression coefficients and individual risk scores for each predictor included at the third fill. Poor MPR at that time (MPR-3) and a drug regimen of no more than 30 prescriptions per person were the strongest predictors of nonadherence. The type of drug had no effect on adherence. The maximum total risk score was 28. Sensitivity at a total risk score greater than or equal to 17 was 35% and specificity was 87%.

Table 1. Regression Coefficient and Score of Each Predictor Included at the Third Fill

Predictor	Regression Coefficient	Score[a]
MPR-3 ≤80% (n = 606)	1.29	13
Number of prescriptions ≤30 in 1 y (n = 1173)	0.82	8
Number of drugs used <20[b] (n = 3220)	0.38	4
Age ≤60 y (n = 1033)	0.33	3
Maximum score		28

MPR-3 = medication possession ratio at third fill.
[a]The score per predictor is obtained by multiplying the regression coefficient by 10, rounded to the nearest integer.
[b]Includes antibiotics and other short usage drugs between fills 1 and 5.

Old age and a drug regimen consisting of fewer medications have previously been associated with poor drug adherence.[4,5]

If we choose a cut-off total risk value of at least 17, our model improves efficiency in identifying nonadherence from 16% to 35%. This means that an adherence improvement strategy directed at the total population of this study could theoretically be useful for 16% of patients, while the same strategy could be applicable to 35% of patients when using our model. The number needed to screen is therefore 5.2 (1/[0.35–0.16]), meaning that we would have to screen 5.2 cases with our model to identify one who was poorly adherent.

Our model has limitations. For example, we do not know the proportion of delayed refills due to a patient's hospitalization or inability to visit the pharmacy. Further development and validation in other healthcare systems are needed.

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