ORIGINAL RESEARCH

Effects of Comorbidity and Clustering upon Referrals in Primary Care

Frederick M. Chen, MD, MPH, George E. Fryer, Jr., PhD, and Thomas E. Norris, MD

Objective: **To examine the effect of patient characteristics and comorbidity on referrals in primary care.**

Methods: **Cross-sectional analysis of patient encounters and referrals during a 1-year period for a primary care network of 9 clinics. The analysis adjusted for the clustering effect of physicians and clinics on the data.**

Results: **23,720 specialty referrals were generated from 251,240 patient encounters, resulting in a total referral rate of 9.4 referrals per 100 encounters. Age, gender, and certain comorbid conditions were significant predictors of referral for any given encounter.**

Conclusions: **Patient characteristics and comorbidity are predictors of referral. Studies of primary care processes need to account for clustering of physicians and clinics in their research design. (J Am Board Fam Pract 2005;18:449–52.)**

In this era of rising health care costs and increasing emphasis on patient safety, surprisingly little is known about patients' transition from primary to specialty care. Many explanations have been offered for the documented large variations in referral rates.[1–3] Comorbid conditions and patients' overall health status are clearly associated with the decision to refer,[4–6] but there is also evidence that referral rates are also related to patient preferences and demographic factors.[7,8] At another level, attributes of health care provider personnel and facilities, and the systems in which they work have been found to be predictors of patient referral.[9–13] Utilization review and reimbursement mechanisms are systemic variables that influence referral patterns.[14,15] The interplay of these multiple factors in the referral process is complex and continues to defy any simple explanation. We focused our analysis on a few critical predictors—patient characteristics and comorbidity—while introducing the use of multilevel analysis in referral research.

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From the Department of Family Medicine, University of Washington, Seattle, WA (FMC, TEN); and Department of Pediatrics, University of Rochester, Rochester, NY (GEF).

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Corresponding author: Frederick M. Chen, MD, MPH, Department of Family Medicine, University of Washington, 4311 11th Avenue NE, Suite 210, Seattle, WA 98195-4982 (e-mail: fchen@u.washington.edu).

There is growing recognition of the importance of multilevel analysis when analyzing clustered and nested data.[16–19] Failing to account for the multilevel structure of patients, providers, and clinics may underestimate standard errors or result in inefficient estimates. Recognizing that the theoretical model of the referral process is complex and multifactorial, we chose to focus on a few significant predictors of referral. These were patient characteristics, comorbidity, and the clustering effect of primary care data. In this study, we sought to examine the contribution of comorbidity, as measured by individual ambulatory diagnostic groups (ADGs), to physician referral tendencies, and to identify characteristics of patients most likely to be referred. We hypothesized that comorbidity, as measured by ADGs, would have a strong influence on referral likelihood, even after adjusting for clustering.

Methods

Setting

The University of Washington Physicians Network (UWPN) is a primary care network of 9 clinics, distributed throughout the Puget Sound region. The UWPN employs over 80 family physicians, internists, pediatricians, and mid-level providers. One unique aspect of the UWPN is the use of a electronic health record system, EPIC (Epic Systems Corporation, Madison, WI). This database captures all patient contacts including office visits, referrals, billing, subsequent visits, laboratory and medication orders, and visit diagnoses. With the approval and cooperation of the UWPN research committee, the UWPN information technology office provided records of all clinic encounters that took place in 1999. Telephone encounters and duplicate encounters that occurred on the same day were excluded. Encounters with providers who had fewer than 100 patient contacts were also excluded. Personal identifiers were removed from the data set. The University of Washington Institutional Review Board reviewed and approved this study.

Subjects

The unit of analysis was an individual patient encounter. Encounters, rather than individual patients, were examined to assess the independent effect of patients' comorbid conditions on the likelihood of referral.

Measures

Dependent

A referral was defined as an encounter that resulted in a consultation to another physician for specialty care.

Independent

The Andersen-Newman model of access to care, which includes predisposing, enabling, and need factors, was selected as the conceptual basis for our analyses.[20,21] Predisposing factors include age, gender, race, and ethnicity. Enabling factors such as income were not available in this secondary data set. In addition, all UWPN patients have health insurance, so they are homogeneous on this enabling factor. The need factor assessed in this study is case mix.

To assess the role of burden of illness in the decision to refer we used the Johns Hopkins ACG (Adjusted Clinical Group) assignment software.[22,23] This software was developed in the 1980s to evaluate the relationship of patient morbidity to the cost and utilization of health care services. The package assigns each patient's ICD-9-CM diagnostic codes to a unique ADG. We used the ADGs because ADGs explain more of the variation in resource use than the ACG indicators.[4,10]

Analyses

System level factors also influence referral patterns. For example, we observed considerable variance across the 9 study clinics in rates of referral, from 5.8 to 13.6%. In addition, physicians were substantially, although not totally, nested within clinic. Accordingly, SUDAAN software (Research Triangle Institute, Chapel Hill, NC) was used to perform all analyses. Its robust variance estimator accounts implicitly for any number of stages of nesting within the primary clusters (clinics), including in this case, physicians and individual patients. Initially, bivariate tests were done to evaluate the relationship of age, gender, race, and ADG with referral. Then, individual ADGs were examined for their effect on referral likelihood after adjusting for individual patient characteristics in separate logistic regression models. We calculated "design effects" to determine how much of the variance in the estimated effects of the ADGs on referral was because of clustering: both intra-cluster correlation and cluster size. The design effect is a measure of the statistical need to account for nesting.

Results

During 1999, there were 251,240 patient encounters in the 9 clinics. Those encounters resulted in 23,720 specialty referrals, resulting in a total referral rate of 9.4 referrals per 100 encounters. Referral rates varied according to the individual patient characteristics for each encounter (Table 1). Male patient encounters had higher referral rates than female encounters (9.95 vs 9.11, $P = .02$). Encounters with patients >65 years of age and <18 years of age were less likely to result in a referral (10.82 vs 6.73 and 7.24, respectively, $P = .001$). Encounters with minority patients were less likely to result in a referral than encounters with white patients ($P = .002$).

Table 1. Referral Rates by Patient Characteristics

	N	Percentage Referred	χ^2	*P* Value
Age group			33.91	.001
Under 18	62,027	6.73		
18 to 64	163,359	10.82		
65+	25,854	7.24		
Gender			8.02	.022
Female	152,269	9.11		
Male	98,967	9.95		
Race			62.81	0.002
White	169,020	9.86		
African American	12,370	9.07		
Latino	6,241	8.27		
Asian	15,739	7.91		
Unknown	17,312	9.24		

Adjustment for patient characteristics on comorbidity using the ACG software revealed significant predictors of referral. When analyzed independently, 21 of the 32 ADGs were significantly related with referral for any given patient encounter. When the demographic characteristics and ADGs were combined in a logistic regression model, the age and gender characteristics remained significant, and the number of significant ADGs was reduced to 19 (Table 2).

Finally, although we were not interested in the role of the clinic beyond statistically controlling for its influence, its design effect was typically large on all predictors, indicating the need for the nested procedures invoked in the analysis. The average design effect for the ADGs that appear in Table 2 was 5.27. Thus, the SUDAAN procedure adjusted for a >5-fold increase in the variance of their estimated regression coefficients because of clustering.

Table 2. Adjusted Diagnostic Group (ADG) Referral Rates and Odds Ratios for Referral Controlling for Age Group, Gender, and Race

ADG	Referral Rate	Odds Ratio	(95% C.I.)
Time limited			
Minor	9.30	1.01	(0.96, 1.06)
Minor-primary infections	7.99***	0.76	(0.71, 0.82)
Major	11.13*	1.19	(1.07, 1.33)
Allergies	8.55	0.89	(0.77, 1.02)
Asthma	9.30	0.97	(0.87, 1.08)
Likely to recur			
Discrete	8.21*	0.85	(0.72, 1.01)
Discrete infections	11.13***	1.24	(1.15, 1.33)
Progressive	8.19**	0.86	(0.78, 0.94)
Chronic medical			
Stable	8.97	0.97	(0.73, 1.31)
Unstable	10.30*	1.10	(1.02, 1.18)
Chronic specialty			
Stable-orthopedic	10.39	1.16	(1.00, 1.34)
Stable-ent	16.84**	1.83	(1.35, 2.47)
Stable-eye	16.15*	2.03	(1.29, 3.19)
Unstable-ent	13.33*	1.41	(1.11, 1.78)
Unstable-eye	13.48*	1.60	(1.08, 2.38)
Injuries/adverse effects			
Minor	10.07	1.03	(0.93, 1.14)
Major	11.61***	1.25	(1.14, 1.38)
Psychosocial			
Time limited, not severe	11.82**	1.29	(1.13, 1.48)
Persistent/recurrent-stable	10.20	0.99	(0.87, 1.11)
Persistent/recurrent-unstable	10.87**	1.11	(0.99, 1.26)
Signs/symptoms			
Minor	9.49	0.91	(0.82, 1.00)
Uncertain	9.98*	1.12	(1.04, 1.21)
Signs/symptoms			
Major	11.07**	1.29	(1.18, 1.41)
Discretionary	10.22*	1.14	(1.07, 1.22)
See and reassure prevention	11.99***	1.31	(1.22, 1.40)
Administrative	10.33	1.10	(0.96, 1.25)
Malignancy	8.53***	0.79	(0.72, 0.86)
Pregnancy	14.31**	1.77	(1.43, 2.19)
Dental	7.87	0.73	(0.56, 0.95)

* $P < .05$.
** $P < .01$.
*** $P < .001$.

Discussion

This study confirmed the variations in referral rates described by previous work. Identifying and measuring the strength of contributing factors is important in analyzing referral rates and the performance of systems of primary care. This study also demonstrates that data from electronic health records can be used to perform analyses of common primary care processes.

Comorbidity analysis remains an important tool in primary care research. This study shows the value of the ACG system in predicting the effect of patients' comorbid conditions on referral. One unique aspect of the study was the individual analysis of ADGs and their independent predictive utility. Although most researchers combine ADGs into the ACG system and sum the burden of disease scores, these results suggest that there is value to examining individual ADGs when there are sufficient data to do so.

In examining the results of this study, encounters with ADGs that signified urgent or unstable conditions were more likely to result in referral. Similarly, encounters with ADGs that reflected specialty oriented care were also more likely to be referred. These findings suggest that subsets of ADGs may be used as a means of monitoring trends in referral patterns.

This study also reinforces the value of multilevel analysis and modeling in examining complex processes in primary care. Many primary care research study designs introduce clustering or nesting into the data structure. For primary care, in which research studies are often conducted in multiple clinical sites or practice based research networks, multilevel analysis may prove to be a useful tool.

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