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Refereed paper

When your words count: a discriminative model to predict approval of referrals

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ABSTRACT

Objective To develop and test a statistical model which correctly predicts the approval of outpatient referrals when reviewed by a specialty service based on nine discriminating variables.
Design Retrospective cross-sectional study.
Setting Large public county hospital system in a southern US city.
Participants Written documents and associated data from 500 random adult referrals made by primary care providers to various specialty services during the course of one month.
Main outcome measures The resulting correct prediction rates obtained by the model.
Results The model correctly predicted 78.6% of approved referrals using all nine discriminating variables, 75.3% of approved referrals using all variables in a stepwise manner and 74.7% of approved referrals using only the referral total word count as a single discriminating variable.
Conclusions Three iterations of the model correctly predicted at least 75% of the approved referrals in the validation set. A correct prediction of whether or not a referral will be approved can be made in three out of four cases.

Keywords: outpatient referral, prediction rates, statistical model

Introduction

An outpatient referral in health care can be defined as the process that results in the transfer of patient care from a referring provider to a secondary service or provider, and the return of patient care to the referring provider when and if appropriate.[1] Referrals in the outpatient setting are essential components of primary care. In general, referrals can help by facilitating diagnosis or management, by allowing primary care providers to request specialised procedures, or by providing second opinions from specialists.[2] Previous studies have shown referral rates vary among different healthcare systems.[3,4] For example, in the UK it is estimated that approximately 13.9% of the total patients seen by primary care providers each year are referred, while in the USA between 30% and 36% of patients visiting primary care settings each year are referred to specialists.[3,5] Referrals in the outpatient setting are healthcare processes that are susceptible to breakdowns.[6–11] Breakdowns in the referral process can result in poor continuity of care, slow the diagnostic process,[6] cause delays to and repetition of diagnostic tests,[7] contribute to polypharmacy,[6] increase litigation risk, cause patient and provider dissatisfaction and promote loss of confidence in providers. Referral breakdowns threaten the quality of care.[8–11] Efforts to prevent breakdowns, and to improve and control the referral process across different settings have been reported; these include those using incentive schemes[2,12] and those relying on the use of information technologies to support effective referral communication.[13] Incomplete medical work-ups may result in deferring a decision by the specialist to approve the referral, until an appropriate work-up is completed.[14] Thus, assessing the appropriateness and completeness of the patient's medical work-up by reviewing each referral before it reaches the specialist has proved to be an essential step in effective referral processes.

In an effort to minimise breakdowns in the referral process, healthcare organisations have explored a variety of interventions, including implementing complex referral incentive programs,[15,16] adopting referral guidelines, using comprehensive referral templates,[17,18] providing referral services based on telemedicine technology[19] and automation of the referral process using web services.[20] However, to our knowledge, no statistical models about the referral process have been developed and tested. As part of a larger quantitative and qualitative study of referrals, aimed at developing methods to assess written outpatient referrals and their outcomes, we developed and tested a model to predict the approval of referrals in a large public county hospital system in a southern US city. The aim of the model is to statistically distinguish referrals that will be approved from those that will be denied when reviewed by the specialty service.

Methods

We extracted 500 random anonymised referrals from a sample of referrals made to surgical specialties (55%), medical specialties (26%), other supportive specialty services (12.4%), obstetrics and gynaecology (6%) and mental health services (0.6%). We included only referrals of adult patients. Primary care providers wrote the referrals using an electronic medical record between 1 and 31 October 2007. The random sample represented approximately 1% of the total referrals made by providers for that period. Each referral included basic demographics, free-text comments entered by the primary care provider, a reason for referral and the associated diagnoses. We collected additional variables related to each referral. For this study we included a total of nine potential discriminating variables and the outcome of the review of each referral by a specialty service (i.e. approved or denied) (see Table 1).

We divided the sample into two sets, a training set and a validation set, to validate the model. We randomly selected 200 of the 500 referrals to use in the training set. We entered the data for all 500 referrals into the statistical software SPSS ® for Windows (Rel. 16.01. 2007. Chicago: SPSS Inc). We used the Rankit method to calculate normalised values for the variables with non-normal distributions in SPSS ®. We created a discriminative function as the basis for the statistical model. Discriminative functions are created to predict group membership based on linear combinations of a set of predictor variables. We used all nine available referral variables to calculate the discriminative function in the first iteration of the model. Subsequent iterations of the model used a stepwise method introducing one variable at a time to identify and select the set of variables with the highest discriminating power. Finally, we created a single predictor model using the variable with the highest discriminative power based on the size of the variable's correlation within the model. For validation purposes, we classified the remaining 300 referrals in the validation set using each of the various iterations of the model. We compared the correct discrimination rates of all the model iterations.

Results

Table 2 shows a summary of the referral data used in this analysis. Using all nine variables to classify the

Table 1 Available referral discriminating variables

Variable	Type	Value(s)
Referral review outcome	Nominal	Approved/denied
Age	Continuous	
Gender	Nominal	Male/female
Priority	Nominal	Regular/urgent
Provider's comment word count* (WC-MDComment)	Continuous	
Reason for referral word count* (WC-Reason)	Continuous	
Referral total word count* (WC-Total)	Continuous	
Time elapsed from referral creation to referral review* (T-ReferralReview)	Continuous	In days
Time elapsed from referral review to decision* (T-ReviewDecision)	Continuous	In days
Time elapsed from referral creation to referral decision* (T-ReferralDecision)	Continuous	In days

* Variables with non-normal distributions

Table 2 Referral data summary: *n*=500

			Training set (*n*=200)		Validation set (*n*=300)	
			Denied	Approved	Denied	Approved
Review outcome			144 (72%)	56 (28%)	212 (70.7%)	88 (29.3%)
Gender			Male 78 (39%)	Female 122 (61%)	Male 107 (35.7%)	Female 193 (64.3%)
Priority			Regular 196 (98%)	Urgent 4 (2%)	Regular 291 (97%)	Urgent 9 (3%)
	Mean	Min	Max	Mean	Min	Max
Age	51.64	6	81	50.34	3	85
WC-MDComment	65.72	0	2196	70.60	0	2070
WC-Reason	48.98	1	295	59.37	2	435
WC-Total	111.90	1	2208	124.84	2	2205
T-ReferralReview	3.16	0	56	5.65	0	370
T-ReviewDecision	10.75	0	113	12.05	0	113
T-ReferralDecision	13.92	0	113	17.71	0	370

training set, the model correctly predicted approved referrals in 76.4% of the cases in a single step; when using all variables in a stepwise manner, introducing one variable at a time, the model correctly classified approved referrals on 71.5% of the cases. The referral total word count and the time elapsed from the creation of the referral until the review by the specialty service were the two variables with the highest discriminative power. However, the referral total word count was the variable with the highest discriminative power, with an absolute correlation within the model of 0.704. The model correctly identified approved referrals 71% of the time in the training set using the referral total word count as a single predictor. When validating the model using the data from the referrals in the validation set, the model correctly identified 78.6% of the approved referrals using all nine variables, 75.3% in the stepwise iteration and 74.7% using the referral total word count as the single predictor. Table 3 shows the calculated discriminative coefficients for the variables used in the model in all three iterations. Table 4 shows a summary of the classification results comparing the results when using both the training set and the validation set for the various iterations of the model.

Discussion

All three iterations of the model resulted in a correct discrimination rate of approximately 75% when used to analyse the validation set. This means the model predicted in three out of four cases whether a referral was approved when reviewed by a specialty service. The highest correct approval prediction rate (78.6%) was obtained when using all nine discriminating variables; however, using just the referral total word count as a single predictor resulted in a 74.7% correct referral approval prediction rate.

In practice, the high correct prediction rate achieved when all the variables were used in the model may prove to be useful only in a limited set of circumstances (i.e. research). Collecting a large number of variables on each referral is difficult; hence the advantage of developing models using fewer variables as in the second and third iteration of our model. Statistical predictive models like the one described in this study can have practical clinical implications. For example, developers of information systems designed to support clinical communication could incorporate these types of models as part of their functionality to provide basic decision support to clinicians. A referring provider could be asked to provide more context (i.e. more information) for a particular case before the referral is submitted for review if the referral does not meet the threshold predicted by the model. A discriminative variable such as the total word count is simple, easy to calculate and use and, as demonstrated here, when combined with other context-specific variables it can become a powerful discriminative predictor.

Evaluating referrals is difficult because of the great variability in the way they occur in different settings. Identifying referral indicators that are common across different settings can potentially allow comparative and predictive studies. The use of a simple and readily available indicator may be a convenient way to quickly assess whether or not a referral will be processed

Table 3 Canonical discriminative coefficients

	Model iteration 1: all nine variables	Model iteration 2: variables – stepwise	Model iteration 3: total word count
Gender	–0.505		
Priority	0.000		
Age	–0.245		
WC-MDComment	0.145		
WC-Reason	0.703		
WC-Total	0.217	1.027	1.096
T-ReferralReview	–0.288	0.616	
T-ReviewDecision	–1.398		
T-ReferralDecision	1.213		
Constant	0.602	0.114	0.093

Table 4 Model classification results

Iteration 1 All variables in a single step[a,b]

			Predicted group membership		
		Review outcome	Denied	Approved	Total
Training	Count	Denied	19	37	56
		Approved	11	133	144
	%	Denied	34.5	65.5	100.00
		Approved	7.6	92.4	100.00
Validation	Count	Denied	32	56	88
		Approved	9	203	212
	%	Denied	36.8	63.2	100.00
		Approved	4.2	95.8	100.00

[a] 76.4% of training cases correctly classified
[b] 78.6% of validation cases correctly classified

Iteration 2 All variables stepwise[c,d]

			Predicted group membership		
		Review outcome	Denied	Approved	Total
Training	Count	Denied	9	47	56
		Approved	10	134	144
	%	Denied	16.1	83.9	100.00
		Approved	6.9	93.1	100.00
Validation	Count	Denied	22	66	88
		Approved	8	204	212
	%	Denied	25.0	75.0	100.00
		Approved	3.8	96.2	100.00

[c] 71.5% of training cases correctly classified
[d] 75.3% of validation cases correctly classified

Iteration 3 Using only referral total word count[e,f]

			Predicted group membership		
		Review outcome	Denied	Approved	Total
Training	Count	Denied	8	48	56
		Approved	10	134	144
	%	Denied	14.3	85.7	100.00
		Approved	6.9	93.1	100.00
Validation	Count	Denied	19	69	88
		Approved	7	205	212
	%	Denied	21.6	78.4	100.00
		Approved	3.3	96.7	100.00

[e] 71.0% of training cases correctly classified
[f] 74.7% of validation cases correctly classified

appropriately. The total referral word count probably reflects the amount of context that the referring provider is including in the referral. In related work that we have conducted as part of a larger study of the referral process, we assessed the referral communication word by word and found that the more the meaningful clinical context included by the referring provider, the higher the chance of the referral being approved upon review by the specialist. This finding is congruent with the results of similar studies conducted in other fields where written communication was analysed and contextualisation was used as a strategy to achieve effective communication.[21]

Our study is limited by the fact that a single clinical site provided the referrals for the study. Furthermore, a preliminary communication analysis word by word of the referring providers' referral comments seems to provide more robust and discriminative characteristics that could be used to enhance the discriminative power of the word count as a single predictor in future studies. Also, an analysis by specialty service may prove useful in highlighting differences in the way referrals are reviewed by the different services.

Future studies should aim to include a larger number of meaningful potential discriminative variables; also researchers should take advantage of existing local indicators that may prove to be strong discriminative variables in their particular settings. Results of the present study illustrate how simple indicators may help to improve complex healthcare processes such as referrals.

Conclusion

Statistical models designed to discriminate which outpatient referrals are likely to be approved and those likely to be denied by specialists have the potential to help improve the referral process.

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All authors had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

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CONFLICTS OF INTEREST

None.

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