



Predictive Factors for Abnormal Illness Behaviour in Low Back Pain

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Abstract

The objective of this study was to develop a self-administered checklist of behavioural characteristics indicative of abnormal illness behaviour.

A 32-item questionnaire was distributed to 237 consecutive patients with primary complaints of low back pain in 15 rehabilitation facilities across Canada.

Multivariable (forward stepwise) logistic regression revealed 5 key predictors of abnormal illness behaviour:

- 1) blaming others for his/her situation,
- 2) negative family / workplace / social situations,
- 3) receiving financial compensation,
- 4) involved in litigation and
- 5) sleep disturbance.

For those with fewer than 3 predictors the chance of abnormal illness behaviour was less than 40%. The chance of abnormal illness behaviour jumped to more than 98% for those with 4 or more predictors. This validated questionnaire is both sensitive and specific.

Key words: abnormal illness behaviour, questionnaire, back pain, logistic regression, predictor, validation

Introduction

Psychological and behavioural changes are a normal, universal human response to pain. Mechanic¹ coined the term illness behaviour to denote the way individuals perceive, evaluate, and react to painful sensations.

The importance of psychological distress and illness behaviour is well recognized in low-back pain.² While most individuals are able to resolve or significantly reduce their pain experience either spontaneously or through suitable treatment, some patients react inappropriately to the original nociceptive pain stimulus in the motion segment and develop abnormal, non-physiologic behavioural and psychological responses. When this occurs, the dominant disability is no longer primarily musculoskeletal and the medical explanation for the physical symptoms is secondary. For this subset of patients the presentation is influenced significantly by superimposed psychosocial factors, and motor performance does not necessarily reflect physical capacity or structural limitations of neuromusculoskeletal function.

Abnormal illness behaviour exists when psychological distress is communicated in bodily terms and no adequate organic cause can be established for the physical symptoms. It is a maladaptive, persistent mode of experiencing, perceiving, evaluating or responding to one's own state of health.³

Patients whose low back pain is one manifestation of such abnormal illness behaviour present a diagnostic challenge. Because these individuals have generally not adopted effective pain-coping strategies they exhibit a perplexing mixture of persistent signs and symptoms. Negative attitudes and low expectations create disease conviction and strong resistance to clinicians' reassurance. This typical psychological profile influences the outcome. As a result, chronic low back disability has become a difficult, costly diagnostic and therapeutic dilemma, absorbing considerable medical care.

Psychological characteristics are strong predictors of response to physiotherapeutic treatment. Decades of research and clinical experience with chronic low back patients have generated an extensive catalog of psychosocial manifestations and personality traits characteristic of pain behaviour. A literature review by Cats-Baril and Frymoyer⁴ showed a multitude of predominantly non-biological factors correlated with low back pain disability. Waddell's⁵ signs of non-organic pain behaviour are most likely in the group with greater than 3 months of pain, but these tests have not shown an ability to identify acute patients at risk for abnormal illness behaviour.

Numerous psychometric instruments, including the Modified Somatic Perception Questionnaire⁷, the Zung Depression Scale⁸ and the Illness Behaviour Questionnaire⁹ have been developed to detect psychological disturbances. While these are useful tools to explicate suspected psychological disorders, their length and complexity often deter the busy clinician from using them to screen for the early manifestations of non-organic pain behaviour.

Burton et al.⁶ demonstrated that distress can present early in the course of low back pain, indicating that the psychosocial aspects of disability are not necessarily a function of chronicity. The early identification of patients at risk for pain and distress behaviours leading to chronic disability may help focus treatment and reduce costs.

Using a short, simple questionnaire may help identify those at risk for developing significant psychosocial disturbances and disability. To be clinically useful and cost-effective, the questionnaire would have to improve upon the capability of an experienced examiner to accurately identify incipient pain behaviour. In the acute stage, such a questionnaire might then alert the clinician to patients requiring special attention or additional care.

Purpose

The objective of this study was to develop a self-administered checklist of behavioural characteristics indicative of abnormal illness behaviour among individuals with low back complaints. The goal was to provide clinicians with a simple, brief, comprehensive, easily administered questionnaire to help identify or predict abnormal illness behaviour.

Methods

From November 1 to December 31, 1996, a 32-item questionnaire was distributed to 237 consecutive patients at their initial assessment for a primary complaint of low back pain in 15 physiotherapy rehabilitation clinics across Canada. The authors developed the questions based upon a review of the existing literature, input from an expert panel and personal clinical experience treating chronic pain and illness behaviour patients. All questions required yes / no binary responses. Questionnaires were forwarded to the Canadian Back Institute (CBI) Research Department. Only the 200 completed questionnaires were analyzed.

Experienced physiotherapists examined every patient using a standardized complete history and physical examination to diagnose the pattern of mechanical back pain. The history included information on pain location, intensity, frequency, duration and response to activity. History addressed mechanism of injury, past history and previous treatment. The physical assessment included mechanical and neurological examinations, repetitive movements to establish symptom response and Waddell's non-organic tests.⁵

At the end of the first visit and without reference to the questionnaire, the clinician used a nine item checklist to categorize the patient as exhibiting either abnormal illness behaviour (IB) (study) or no abnormal illness behaviour (control). The checklist was based on the history and the patient's ability to complete the physical examination. Those with at least four positive attributes were diagnosed as having abnormal illness behaviour.

No significant difference was observed between groups for the variables of age and gender. Both were consistent with the average demographics of the general CBI patient population. The overall mean age was 42.5 years (standard deviation 13.5 years, range 18-82 years). In the abnormal illness behaviour group the mean age was 41.7 years (standard deviation 11.5 years, range 23-73 years); in the non-abnormal illness behaviour group the mean age was 42.9 years (standard deviation 14.4 years, range 18-82 years). Males comprised 52% of the total sample, 51% in the abnormal illness behaviour group, 52% in the non-abnormal group.

The clinics used to accumulate patient volunteers are primary access, rehabilitation facilities that focus on pain control in acute, sub-acute and chronic ambulatory populations. Patients typically present with mechanical spinal pain of musculoskeletal origin. Patients with suspected systemic disease or cases resulting from trauma sufficient to produce severe bony injury or major neurological sequelae are referred elsewhere.

Analysis

Statistical analysis was performed using the SAS System for Windows version 6.10 (SAS Institute, Cary, NC, 1993). To reduce the number of variables, eight questions were deleted from the analysis because of the similarity to other questions; two were not analysed because they were open ended questions; three other questions were not analyzed because patients frequently changed the wording of either the questions or the responses; thereby, altering the meaning/intent of the questions.

Regression Modeling

Logistic regression analysis was used to model the relationship between the binary response variable (abnormal illness behaviour present/absent) and the remaining 19 explanatory variables (questionnaire responses coded 0 = no, 1 = yes). Univariate logistic regression analysis was used to identify significant associations between each potential predictor and the dichotomous outcome. An alpha level of 0.05 (two sided) was used as the criterion for statistical significance. The subset of significant univariate predictors was included in a logistic regression to find the best multivariable model predicting the outcome. The values for the unadjusted (univariate) and adjusted (multivariable - forward stepwise) analyses are derived from the Wald test of significance of each covariate.

The potential predictors were entered into the model in a stepwise manner, beginning with the feature that accounted for the largest proportion of the variance of the outcome. In this way it was possible to identify the minimum number of features that had independent prognostic significance.¹¹ Each variable that was not significant in the univariate analyses was added one at a time to the chosen model to find if it then made a significant contribution. Since model selection techniques are exploratory, and because of the criticisms of model selection algorithms¹², the Best Subset Selection method¹³ was also used for model development.

Probabilities

Predicted probabilities were calculated from the binary logistic regression model to estimate the probability that a given individual has abnormal illness behaviour. The probabilities differed slightly depending on which predictive factors from the final model were present. Because of the large number of combinations in this sample, the predicted probabilities were averaged and summarized based upon the presence of any one factor, or combination of factors.

Validation

If the same set of data used to fit the model is used to test the predictive accuracy of the model, it is likely to be positively biased.

Two methods for obtaining a nearly unbiased internal assessment of the predictive accuracy of a model from the original sample are: 1) datasplitting, and 2) receiver operating characteristic (ROC) curve.

- 1) datasplitting – a random sample of approximately two thirds of the completed questionnaires (n=135) was used to develop the model (BUILD sample). This BUILD sample and the remainder of the data were then pooled together (TEST sample) to assess the accuracy of the prediction model.
- 2) ROC curve - a graphic display that measures the predictive accuracy of a logistic regression model over a range of cutoff points. The area under the curve is not an extremely sensitive measure when comparing models but is ideally suited for independent data that are not used to fit the model.¹⁴ A ROC curve was computed for the validation sample (TEST sample).

Results

Modeling

For the 200 patients with fully completed surveys, 70 individuals were independently judged to display abnormal illness behaviour. The randomly selected BUILD sample contained 46 of these patients. Univariate logistic regression on the BUILD sample showed statistically significant increases in odds of abnormal illness behaviour for 14 of the factors in the survey (Table 1).

Table 1:

Univariate logistic regression statistics for the association between individual questionnaire items and abnormal illness behaviour using a 2/3 random sample of the full dataset (BUILD sample)

Variable	Parameter Estimate	Standard Error	Odds Ratio	P-value
1. blaming others	3.6181	0.6583	37.267	0.0001
2. † multiple injuries	0.7043	0.3972	2.022	0.0762
3. financial compensation	2.7535	0.4468	15.697	0.0001
4. deteriorating condition	1.1514	0.3894	3.163	0.0031
5. assistance with personal care	2.0954	0.5575	8.129	0.0002
6. high previous level of activity	1.2384	0.3892	3.450	0.0015
7. constant pain	1.7611	0.4455	5.819	0.0001
8. poor response to medication	1.9643	0.4042	7.13	0.0001
9. sexual dysfunction	2.6266	0.4636	13.827	0.0001
10. multiple consultations	1.509	0.409	4.522	0.0002
11. litigation	2.47	0.5492	11.822	0.0001
12. † in pain > 6 months	0.4521	0.3703	1.572	0.2221
13. currently employed	1.4077	0.5916	4.086	0.0173
14. negative F.W.S. situations	0.9436	0.4829	18.984	0.0001
15. insisting physical diagnosis	1.9985	0.524	7.378	0.0001
16. sleep disturbance	2.509	0.5648	12.293	0.0001
17. † walking aids	0.6817	1.017	1.977	0.5026
18. † age	-0.015	0.0145	0.985	0.299
19. † sex	-0.1476	0.3704	0.863	0.6903

† not statistically significant

F.W.S = family, workplace, social

After controlling for the effects of the other variables, 5 of the predictors remained significant in the multivariable analysis. Five key factors relating to abnormal illness behaviour were: 1) blaming others for his/her situation, 2) negative family/workplace/social situations, 3) receiving financial compensation, 4) involved in litigation and 5) sleep disturbance (Table 2). The Best Subset Selection modeling method confirmed the same 5 predictors as the model with the highest Score value based on the BUILD sample. These were the predictors that were subject to validation.

Table 2:

Forward stepwise multivariable logistic regression of the significant predictors (from Table 1) for the association between individual questionnaire items and abnormal illness behaviour using a 2/3 random sample of the full dataset (BUILD sample)

Variable	Parameter Estimate	Standard Error	Odds Ratio	P-value
1. blaming others for situation	2.6784	0.802	14.562	0.0008
2. negative family/workplace/social situations	2.0757	0.6744	7.97	0.0021
3. receiving financial compensation	2.2481	0.6923	9.47	0.0012
4. involved in litigation	2.3685	0.8617	10.681	0.006
5. sleep disturbance	1.8275	0.8812	6.219	0.0381

The goodness of fit of this model was tested using two measures: 1) Akaike Information Criterion (AIC) and 2) Hosmer and Lemeshow goodness of fit test.¹³ As each of the 5 predictors was added to the baseline intercept only model, the AIC continued to decrease from 125.9 to 80.2, indicating increasing goodness of fit. The Hosmer and Lemeshow goodness of fit test for logistic regression models with binary responses had a value of 4.69 on 5 degrees of freedom ($p=0.4547$) for this model. Thus, the null hypothesis that the model provides a good fit to the data cannot be rejected.

Table 3 shows the predicted probabilities of abnormal illness behaviour for the TEST sample. Only one patient with abnormal illness behaviour had no predictors present. For those with fewer than 3 predictors the chance of abnormal illness behaviour was about 40%. The chance of abnormal illness behaviour increased to more than 98% for those with 4 or more predictors. No patient without abnormal illness behaviour had more than 3 predictors present. Out of the 130 non- abnormal patients, only 4 had 3 predictors.

Table 3a:

Predicted probabilities of abnormal illness behaviour for patients diagnosed with abnormal illness behaviour from the full dataset (TEST sample: $n=70$)

# of predictors present	n	%	mean probability of abnormal illness behaviour	standard deviation
0	1	1.4	0.014	0
1	7	10.0	0.107	0.023
2	12	17.1	0.421	0.014
3	25	35.7	0.826	0.040
4	14	20.0	0.965	0.009
5	11	15.7	0.993	0

Table 3b:

Predicted probabilities of abnormal illness behaviour for patients without abnormal illness behaviour from the full dataset (TEST sample: $n=130$)

# of predictors present	n	%	mean probability of abnormal illness behaviour	standard deviation
0	62	47.7	0.014	0
1	38	29.2	0.108	0.019
2	26	20.0	0.414	0.048
3	4	3.1	0.809	0.034
4	0	0	0	0
5	0	0	0	0

Validation

Datasplitting Method.

All patients with probabilities greater than a minimum cutoff value were classified as abnormal illness behaviour; patients with scores less than the cutoff were classified as non- abnormal (negative). The predictive precision of the derived model is given by the percentage of the fitted groups (in the TEST sample) that were correct.⁶ For the BUILD sample, 91.1 % ([85+38]/135) of the patients were classified correctly by the logistic model (Table 4a). Of the 46 abnormal patients, 82.6% (38) were correctly classified. Only 8 patients with abnormal illness behaviour were mistakenly classified as negative (false negatives). To overcome these biased estimates, the TEST sample was used to evaluate the model. The percentages decreased slightly, as expected; 87.0% ([123+51]/200) of the patients were classified correctly by the logistic model (Table 4b). Of the 70 abnormal illness behaviour patients 72.9% (51) were correctly classified. Only 19 abnormal illness behaviour patients were mistakenly classified as negative (false negatives).

Table 4a:

2 x 2 table of frequency of responses for measuring the predictive accuracy of the logistic regression model using a two-thirds random sample of the full dataset (BUILD sample)

		PREDICTED		
		negative IB	abnormal IB	total
OBSERVED	negative IB	85	4	89
	abnormal IB	8	38	46
	total	93	42	135

Percentages: Correct = 91.1, Sensitivity = 82.6, Specificity = 95.5 probability cutpoint = 0.41

Table 4b:

2 x 2 table for measuring the predictive accuracy of the logistic regression model using the full dataset (TEST sample)

		PREDICTED		
		negative IB	abnormal IB	total
OBSERVED	negative IB	123	7	130
	abnormal IB	19	51	70
	total	142	58	200

Percentages: Correct = 87.0, Sensitivity = 72.9, Specificity = 94.6, Probability cutpoint = 0.41

Correct – probability that the model correctly classifies the data for a chosen probability cutpoint.

Sensitivity - a measure of accuracy for predicting events. It is the proportion of those with abnormal illness behaviour that the model predicts correctly for a chosen probability cutpoint.

Specificity - a measure of accuracy for predicting non-events. It is the proportion of those without illness behaviour that the model predicts correctly for a chosen probability cutpoint.

cutpoint – the point at which all patients with probabilities greater than this value are classified as abnormal illness behaviour; patients with scores less than the cutoff are classified as negative.

IB – illness behaviour

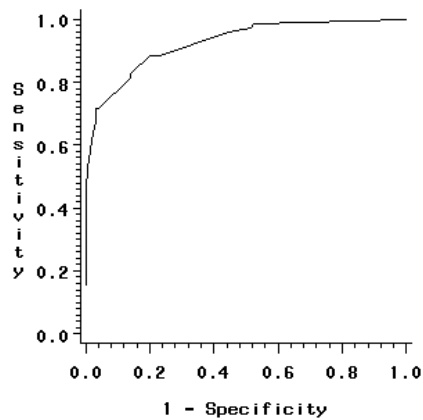
ROC Curve Method.

Figure 1 displays the ROC curve for the TEST sample. The ROC curve rises quickly resulting in a large area under the curve, indicating the model developed using the BUILD sample has high predictive accuracy for the TEST sample.

Figure 1: ROC curve for the TEST sample

Receiver Operating Characteristic (ROC) Curve

Validation on the Full Sample



The dataset used to display the ROC curve lists the estimated event probabilities in descending order so that both sensitivity and 1-specificity increase as the probabilities decrease.
1-specificity = the number of false positives divided by the number of nonevents.

Discussion

The objective of this study was strictly discriminatory and did not attempt to explain associations. Dionne et al.¹⁵ suggested that building the predictive model should focus on the identification of a few variables that can be easily identified and reliably collected in a clinical setting. This strategy resulted in a simple, brief, comprehensive, easily administered questionnaire to help identify abnormal illness behaviour in a sample of low back pain patients.

The quality of many epidemiological studies relies heavily on the accurate measurement of the dependent variable. One potential weakness of this study is that selected physiotherapists, not psychologists, made the clinical decision regarding the presence of abnormal illness behaviour. These therapists received additional training, specific guidelines and had substantial clinical experience to give a reasonable diagnosis if not a definitive opinion.

For this sample, a regression model predicted the probability of abnormal illness behaviour with an accuracy comparable to other prediction studies.^{6,15-17} The validation strategy used two methods of modeling and two forms of validity testing to identify 5 key predictive factors. Future research is required in which the predictors are subjected to external validation on a new independent sample of low back pain patients. This will be an overall assessment of the validity. However, a rigorous epidemiological approach showed consistent results for each of the analysis tools employed. High percent correct, sensitivity and specificity values for the datasplitting technique produced strong validation results for this model. While reliability of a clinical tool is necessary, reliability was not assessed in this study, because these subjects were gathered from a clinical setting where the treatment program was aimed at resolution of pain and disability. Reliability studies involving clinical measures should be conducted among people not receiving care to avoid the treatment program from becoming a confounding variable.

The predictive probabilities and subsequent validation results are strong indications of potential applicability of this model. The presence of one or two of the 5 key predictors placed the probability of abnormal illness behaviour at about 40%. Patients with 4 predictors had a probability of abnormal illness behaviour of 98% while those with all 5 exceeded 99%. For this study, the key predictors within the questionnaire carry powerful predictive ability.

Although patient age and sex were part of the initial modelling strategy, they were not significant predictors and in this sample, abnormal illness behaviour was not affected by these variables. This lack of predictive ability for age and sex has been reported in previous low back pain research.^{4,18-21} Other studies have found 1 or both of these variables to help with prediction.^{11,22,23} The finding that being in pain for more than 6 months had no bearing on the final model is similar to Burton et al.'s⁶ research demonstrating that distress can present early in the course of low back pain.

An important feature of this model is the high sensitivity and specificity, important considerations when choosing any diagnostic test.²⁴ A sensitivity of 1 and a specificity of 0 will classify all observations as events. Conversely, a specificity of 1 and a sensitivity of 0 will classify all observations as non-events. Sensitivity and specificity vary according to the probability value chosen to decide if an observation represents an event or a non-event. A highly sensitive test should be chosen when there is an important consequence for missing a disease. In the context of this study, false positives, labeled with abnormal illness behaviour, may receive more intensive treatment than necessary. False negatives, where the identification of abnormal illness behaviour is missed, may be denied necessary rehabilitation, prolonging recovery. A 0.41 cutpoint resulted in 72.9% sensitivity and 94.6% specificity. Since lowering the probability cutpoint increases the number of false positives as it decreases the number of false negatives, which is the desired effect, the arbitrary cutpoint was set slightly lower than previous research.⁴

Despite its statistical validity, no questionnaire can capture the entire picture. Measurement errors will further decrease precision.¹⁹ The information must be used in conjunction with a thorough clinical assessment. Accurate prognosis for low back pain resolution is partly dependent upon the ability of the treating professional to detect underlying factors that might hinder recovery. The progress of low back pain is highly variable and it will never be possible to eliminate the inherent uncertainty in predicting outcome, but an awareness of significant contributing non-physical factors can help to forecast its course more accurately.

Overly optimistic predictions of back pain risk creating disappointment, anxiety and anger when the patient's recovery does not proceed as planned. Forecasting a strong chance of abnormal illness behaviour may have a negative impact when recovery is uncomplicated.²⁵ the inherent uncertainty of prognostication can never be eliminated but this study identifies patient characteristics associated with a high probability of abnormal illness behaviour.

Clinically, this instrument can be used as an outcome measure to analyze the success of rehabilitation. High proportions of patients with abnormal illness behaviour at discharge may suggest that an alternative or complimentary method of treatment, which promotes positive coping strategies, is required. More appropriately, this instrument can be used to identify, early in the course of treatment, challenging patients in need of more comprehensive rehabilitation. The early initiation of aggressive intervention, such as controlled exercises to reduce illness behaviour¹⁰ and promotion of positive coping strategies, might improve outcomes in the form of shortened periods of incapacity and reduction in the likelihood of chronicity.

With this method for accurately identifying low back pain patients with abnormal illness behaviour, future outcomes research should focus on appropriate treatment strategies for this challenging segment of the back pain population.

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