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Socio-demographic variables are limited predictors of health status in multiple sclerosis

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Abstract *Background and objectives* Self-reported health status measures reflect disease impact from the patient's perspective. However, such measures are not designed for individual patient use and are rarely used to guide clinical practice. Nevertheless, if strong predictors of health status can be demonstrated in large datasets, these could be used to identify people at risk of poor health states and help target interventions. The aim of this study was to examine the predictive value of routinely collected socio-demographic variables on health status. *Method* Data for 638 patients with multiple sclerosis (MS) on the eight health dimensions of the Medical Outcomes Study 36-item Short Form Health Survey (SF-36) were collected either by a postal survey or hospital attendance and analysed by multiple regression analyses. *Results* Several sociodemographic variables, such as unemployment and manual social class had some predictive value on health status, but the effect was not strong (maximum cumulative variance explained 53 %). *Conclusions* Sociodemographic variables that we studied were limited predictors of health status in MS and are of limited value in guiding clinical practice.

Key words multiple sclerosis · socio-demographic variables · health status · SF-36

Introduction

Multiple sclerosis (MS) has an impact on many aspects of health, and warrants comprehensive multidisciplinary services that meet the needs of people with MS [28]. Patient-based health status rating scales reflect disease impact from the patient's perspective and not surprisingly they are increasingly used as outcome measures for clinical trials, audit, and epidemiological studies. However, there is little evidence that they have improved outcomes or patient management [12]. This may be because information from such measures is under utilised. Health status data can provide basic information that highlight areas of health that may require further investigation. These areas may be missed in a normal clinical situation. Thus it can prioritise areas of importance that may require further investigations and targeting by clinicians.

Therefore, if strong predictors of health status can be demonstrated in large datasets, these could be used to identify groups of people at risk of poor health states and aid individual tailoring of interventions. Such predictors should be routinely collected so that identification can be prompt and cost-effective. Sociodemographic variables are thus ideal for this purpose, since they are routinely collected, and readily available.

A previous small study examined the predictive value of socio-demographic variables in MS and found that clinical and socio-demographic variables accounted for a maximum of 50 % variance of health status scores [8]. The current study builds on this work by using multi-

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variate analyses to examine the predictive value of routinely collected socio-demographic factors on health status. The aim was to determine whether socio-demographic variables predict health status in a large sample of people with MS.

Methods

Samples

This was a cross-sectional study. All patients gave their informed consent prior to their inclusion in the study and were derived from three separate sources.

1) a postal survey of 500 randomly selected and geographically stratified members of the Multiple Sclerosis Society of Great Britain and Northern Ireland. This was part of a larger study developing a patient-based outcome measure for multiple sclerosis [14]. Non-responders were sent reminders at three and five weeks.

2) adults with clinically definite MS attending the National Hospital for Neurology and Neurosurgery (NHNN). Full detail of the sampling and the stratification process for this sample are described elsewhere [10]. Briefly, 150 consecutive attenders were recruited from: a weekly outpatient clinic, an inpatient neurological rehabilitation unit, and admissions under a single consultant (AJT).

3) adults with clinically definite MS who were consecutively admitted to the NHNN for rehabilitation and IV steroid treatment (N = 97).

4) a postal survey of people with a confirmed diagnosis of primary progressive MS [27] from a clinical database (N = 119). Non-responders were sent reminders at three and five weeks.

For samples 2 and 3, people were excluded if they had cognitive impairment that precluded reliable completion of questionnaires, other co-morbid disabling disorders, or were not English speaking.

Health status assessment

The Medical Outcomes Study 36-item Short Form Health Survey (SF-36) [29] is a widely used generic measure of health status. Thirty-five of the 36 items are grouped into eight scales: physical functioning, role limitations due to physical problems, bodily pain, general health, vitality, social functioning, role limitations due to emotional problems, and mental health. One item assesses perception of changes in health but is not used to compute scale scores. Methods for computing scores, which range from 0–100, are reported elsewhere [29].

Statistical analyses

Data quality was determined by computing internal consistency (Cronbach's alpha), the percent of missing data for items, and the percent of scale scores that could be computed. Data quality was examined in the postal survey sample (sample 1), hospital-based sample (samples 2 and 3) and primary progressive MS sample (sample 4) separately, and in the pooled sample. The impact of disability on data quality was also investigated by examining data quality in people who walk unaided, people who walk with an aid, and people who use wheelchairs.

Multiple linear regression analysis is a method for investigating the extent to which one or more predictive variables (independent variables, IVs) predict an outcome variable (dependent variables, DV.) A general goal of regression is to identify the fewest IVs necessary to predict a DV where each IV predicts a substantial and independent segment of the variability in the DV [26].

The regression analyses were conducted in two stages. Firstly, correlational analyses (Spearman's rho) were performed between each of the predictor variables and the domain scores. Secondly, all predictor variables that were univariately associated with each of the domain scores ($p \leq 0.20$) were entered into multiple linear regression models (with a backward selection strategy, using the F-statistic with $p < 0.05$ as the criterion of retaining variables in the model). These analyses resulted in a subset of independent variables that, in combination, best predicted each of the domain scores.

Coding of predictor variables

We used the standard approach of coding the variables as either 0 or 1. Social class was categorised using The Office of Population Censuses and Surveys (OPCS) [20] classification of occupations. Variables were coded as follows: Social class: 0 = Social classes I, II and III non-manual, 1 = social classes III manual, IV and V; Ethnicity: 0 = non-white and 1 = white; Education: 0 = without degree/professional qualification, 1 = with degree/professional qualification; Sex: 0 = male, 1 = female; Marital status: 0 = single, divorced, or separated, 1 = married or with a partner; Employment status: 0 = retired, unemployed or student, 1 = employed or self-employed.

Multiple dichotomous categories were created for mobility, age and duration of disease. For level of mobility indoors, the three ordinal categories (walk without aid, walk with an aid and uses wheelchair) were transformed into 2 dichotomous variables. Age was recoded as three ordinal categories (age 20–39, 40–59 and 60 and over). These categories were then transformed into 2 dichotomous variables. Years since diagnosis of MS was also recoded as three ordinal categories (diagnosed 0–9 years ago, 10–19 years ago and 20 years or more ago), then transformed into 2 dichotomous variables. For all three variables, the extreme group (the least disabled group, youngest and the least years since diagnosis) was chosen as the reference level.

Furthermore, the type of sample was investigated as a possible predictor of health status. Although sample 2 and sample 3 appear as distinct groups, clinically there is some overlap as they both consist of inpatients to the same hospital. Therefore, these two samples were combined and the three sources of samples (postal survey, hospital-based and postal survey of PPMS) were studied. Multiple dichotomous categories were created where the above three categories were transformed into 2 dichotomous variables (the PPMS group was chosen as the reference group).

Results

Sample characteristics

A total of 638 questionnaires were completed (sample 1 = 288, sample 2 = 149, and sample 3 = 97; sample 4 = 104). For sample 1, 409 (82 %) questionnaires were returned. Of these, 121 were returned blank. Of those returned blank, 84 were considered ineligible to participate in the study (eg. changed address, deceased). Therefore the response rate was 69 % (409–121/500–84). The characteristics of all people who completed the SF-36 are shown in Table 1. In one of the MS samples from which the data were obtained (sample 2; n = 149), information regarding ethnicity, education, social class and mobility was not collected. Therefore the data for these variables were available for a total of 489 people.

Table 1 Patient characteristics

	MS N (%)
Total	638
Gender	
Female	412 (65.3)
Male	219 (34.7)
Age	
20–39	146 (23.5)
40–59	357 (57.5)
> 60	118 (19.0)
Years since diagnosis	
0–9 yrs ago	309 (50.7)
10–19 yrs ago	200 (32.8)
> 20 yrs ago	100 (16.5)
Ethnicity[a]	
White	464 (95.7)
Others	21 (4.3)
Marital status	
Married or with partner	447 (70.6)
No	186 (29.4)
Employment status	
Working	144 (23.0)
No	482 (77.0)
Education[a]	
Obtained degree or professional qualification	155 (32.6)
No	321 (67.4)
Social class[a]	
Manual social class	185 (40.9)
No	267 (59.1)
Mobility indoors[a]	
Walk unaided	136 (28.9)
Walk with an aid	204 (43.4)
Uses wheelchair	130 (27.7)

[a] Maximum N = 489

Table 2 Percent item non-response and computable scale scores

Sample	N	Item non-response %	Percent computable scores
Total	638	0.6–5.0	95.3–100
Postal survey	288	1.0–7.3	92.4–100
Hospital-based	246	0.0–2.4	99.2–100
PPMS	104	0.0–5.8	94.2–100
Walk unaided	136	0.0–2.9	97.1–100
Walk with an aid	204	0.5–5.4	94.6–100
Wheelchair	130	1.5–12.3	90.0–100

Data quality

Internal consistency for the postal survey (0.89), hospital-based sample (0.84) and PPMS samples (0.87) suggested consistent responses. Table 2 presents percent item non-response and percent computable scores (indicators of data quality). As expected, the hospital-based samples had fewer missing data than the postal survey sample and the primary progressive postal survey sample. In wheelchair-dependent participants, the proportion of missing data reached a maximum of 12.3 for 1 item. Scale scores were computable for the majority of people.

Socio-demographic predictors of SF-36 scores in people with MS

The magnitude of the correlations among the predictor variables was only weak to moderate. Table 3 shows the final multivariate models after each predictor associated with each of the SF-36 dimensions in a correlational analysis ($p < 0.20$) [16] were entered into backward regression model ($p < 0.05$ for deletion). The correlational matrix and the results of the univariate regression analyses are available from the author on request.

In the final multivariate models, walking with an aid was a significant predictor of poorer health in several dimensions: poorer physical functioning, role physical, bodily pain, vitality and mental health scores. Wheelchair use, on the other hand, predicted poorer physical functioning, bodily pain, and social functioning.

Unemployment was a significant predictor of all health dimensions except bodily pain and mental health. Manual social class was a significant predictor of poorer general health perception, role emotional and mental health scores. Being diagnosed for less than 10 years significantly predicted poorer social functioning and mental health scores.

Although not associated with any other health domains in the final model, being male was a significant predictor of poorer general health perception scores, and lower education level was a significant predictor of poorer bodily pain scores. Ethnicity, marital status and age were not included in any of the final multivariate models.

The adjusted R^2 indicate that 53 % of the variance of physical functioning scores was explained by the variables in the final model: walking with aid, using wheelchair, and being in employment. For the role physical dimension, walking with an aid and employment explain 13 % of the variance. However, for the other dimensions, the variables in the final model explain less than 10 % of the score variance.

In the multivariate models including the type of sample (univariately associated with the domain score) as predictors, both the community ($B = -9.7$; $p < 0.001$) and hospital-based sample ($B = -8.5$; $p < 0.01$) had significantly worse general health scores than patients with PPMS. Similarly, both the community ($B = -11.5$; $p < 0.001$) and hospital-based sample ($B = -11.0$; $p < 0.01$) had significantly worse vitality scores than patients with PPMS. (Full details of these additional analyses are available from the authors on request).

Table 3 Multivariate regression analyses for SF-36 domains with unstandardised coefficients

	PF Multivariate[a] Coefficient´ (95% CI)	RP Multivariate[a] Coefficient (95% CI)	BP Multivariate[a] Coefficient (95% CI)	GH Multivariate[a] Coefficient (95% CI)	VT Multivariate[a] Coefficient (95% CI)	SF Multivariate[a] Coefficient (95% CI)	RE Multivariate[a] Coefficient (95% CI)	MH Multivariate[a] Coefficient (95% CI)
Constant	42.5 (39.0–45.9)	22.5 (18.1–26.9)	59.3 (3.8–15.7)	40.4 (35.9–44.9)	35.6 (32.3–38.9)	48.8 (44.0–52.7)	54.0 (47.5–60.4)	67.7 (64.2–71.3)
Mobility								
Walk with aid	−29.1 (−33.1–−25.0)	−16.0 (−22.0–−9.9)	−12.8 (−19.4–−6.2)		−6.9 (−11.4–−2.4)			−4.7 (−11.1–−2.7)
Uses wheelchair	−40.2 (−44.9–−35.4)		−11.8 (−19.2–−4.4)			−15.6 (−22.2–−8.9)		
Walk without aid[b]	1.0	1.0	1.0		1.0	1.0		1.0
Social class								
Manual occupation				−9.0 (−13.8–−4.2)			−10.3 (−19.7–−1)	−6.8 (−8.8–−0.6)
Non-manual occupation[b]				1.0			1.0	1.0
Ethnicity								
White								
All other ethnicity[b]								
Education								
Degree or equivalent qualification			9.8 (3.8–15.7)					
No degree or equivalent qualification[b]			1.0					
Sex								
Women				6.7 (1.8–11.6)				
Men[b]				1.0				
Marital status								
Married or with partner								
Single/divorced/widowed[b]								
Employment								
Working	10.5 (6.3–14.6)	18.8 (11.8–25.8)		7.4 (1.9–12.9)	7.5 (2.3–12.7)	11.3 (4.3–18.3)	11.3 (0.7–21.9)	
Not working[b]	1.0	1.0		1.0	1.0	1.0	1.0	
Age								
40–59								
60 +								
20–39[b]								
Years diagnosed								
10–19 years						7.8 (1.6–13.9)		4.6 (0.2–9)
20 years +								
0–9 years[b]						1.0		
	adj $R^2 = 0.53$ $F = 143.87$	adj $R^2 = 0.13$ $F = 30.6$	adj $R^2 = 0.06$ $F = 9.8$	adj $R^2 = 0.06$ $F = 9.3$	adj $R^2 = 0.04$ $F = 9.53$	adj $R^2 = 0.09$ $F = 14.2$	adj $R^2 = 0.02$ $F = 5.0$	adj $R^2 = 0.05$ $F = 7.0$

[a] variables in final model; [b] reference group

PF physical functioning; *RP* role physical; *BP* bodily pain; *GH* general health perceptions; *VT* vitality; *SF* social functioning; *RE* role emotional; *MH* mental health

Discussion

Data quality of the SF-36 is somewhat compromised when the SF-36 is administered by postal survey and in more disabled people. This has been discussed before [13]. Furthermore, the sociodemographic variables that we studied were poor predictors of health status. The final model accounts for only around 50 % of the variance for the physical functioning dimension, and 2–13 % for the other domains. Of the variables we studied, walking with support, unemployment and social class were consistently the best predictors of poor health status. It is not surprising that the final model explains substantially more variance for the PF dimension than for any other dimension as it is closely related to mobility levels.

Most socio-demographic variables that predicted health status appeared to be both intuitively correct and have the appropriate effect in terms of the direction of the relationship. Perhaps surprisingly, age and duration of MS were not significant predictors of health status. As social support is an important predictor of quality of life [7], marital status might be expected to be a strong predictor. This was not supported, perhaps because marital status does not indicate quality of social support. Furthermore, there is evidence from a large non-MS population that marital status has little independent effect on health status [9].

For the most part, the type of sample did not predict health status, except that people with PPMS reported better general health and vitality. This finding is difficult to explain, although we have also previously found that people with PPMS reported better psychological impact of MS (measured by the Multiple Sclerosis Impact Scale) compared to other hospital-based samples [23].

Our findings support results from other studies. The study by Brunet et al. [8] demonstrated that sociodemographic and clinical variables explained between 10 % (general health perceptions) and 48 % (physical functioning) of the variance in SF-36 scores. Others have demonstrated associations between unemployment and poor quality of life [5], found low social class to be predictive of worse prognosis [21], and did not find associations between pain and age, sex, or duration of MS [4, 25]. Research from other diseases has demonstrated a similar association between pain and educational level [18]. Our study provides further evidence that demographic and social classification variables only have a modest influence on self-assessments of health [19, 1].

The findings of this study raise questions as to which variables predict health status. Some recent studies have begun to address this question. Self-reported depression is one variable that may be closely associated to health status scores in people with MS. Depression has been shown to be a stronger predictor of quality of life ($r^2 = 0.43$) than EDSS ($r^2 = 0.29$) in a sample of 60 people with MS [11]. In the same study, demographic variables such as duration of illness and age were not strong predictors of quality of life [11]. In another recent study [2], depression was the best predictor of physical health, followed by fatigue and mobility (EDSS). These variables were independent predictors of physical health ($r^2 = 0.65$). The main determinants of mental health scores were depression and fatigue ($r^2 = 0.67$). In other illnesses, studies have found other variables such as social support [6], coping styles [24] and self-efficacy [3] to be associated with quality of life.

The results of this study have useful clinical implications. They indicate that clinicians are unable to identify accurately, from routinely collected socio-demographic variables, individual patients with MS who are at risk of poor health status. This is unfortunate as data from health status questionnaires, using current methods of analysis, are not accurate enough for individual patient clinical decision making as confidence intervals around individual patient scores are wide. This inhibits the value of health status data to individually-tailored care packages. One potential solution to this problem is to analyse health status data using new psychometric methods such as Rasch analysis [22] which claim to generate accurate measures for individual patients. Early evidence supports this claim [15].

This study has two limitations. First, it is cross-sectional. The changing health impact of MS has not been studied and, indeed, remains largely unknown. For example, it has been shown that changes found on magnetic resonance imaging (MRI) are better predictors of disability in MS than baseline MRI [17]. Thus, longitudinal studies are required to determine change in health status. The timing of such evaluation should ideally begin at onset. The rate of deterioration of physical function could be hypothesised to be associated with poor health status. Second, we have used a generic health status measure that was developed for health insurance purposes in the general population. As such it may not address important areas of health that are specific to people with MS.

In conclusion, although a number of socio-demographic variables, such as unemployment and social class were consistently identified to have some predictive value on health status, they are of limited value in guiding clinical practice. Future research should aim to continue the identification of variables that predict health status in MS. The usefulness of health status measures in clinical practice should also be assessed. It is anticipated that such data from group and individual level can be used to assist and influence clinical decision making.

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