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Predictors of vocational status among persons with multiple sclerosis

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ABSTRACT

Background: Multiple Sclerosis (MS) is a common cause of neurological disability in young to middle-aged adults, resulting in physical, psychosocial, and cognitive impairments. Manifestation of these symptoms during crucial work-life years can greatly influence the ability of persons with (PwMS) to retain employment. It is unknown what factors are most important in leading to work disability, and if/how these different factors interact with each other and result in work disability.

Objective: To determine significant predictors of vocational status among PwMS using a structural equation modeling approach.

Methods: A retrospective chart review identified PwMS at an academic tertiary care hospital. The following data was collected: demographics and disease characteristics, vocational status, physical disability status (Expanded Disability Status Scale, EDSS), fine motor function (Nine Hole Peg Test, NHPT), generalized fatigue (Fatigue Severity Scale, FSS), mood and anxiety symptoms (Hospital Anxiety and Depression Scale, HADS) and cognitive function (Symbol Digit Modalities Test, SDMT). An exploratory structural equation model (SEM) was developed to examine the predictive utility of clinical and psychosocial variables on vocational status after controlling for demographic and disease characteristics. The fit of the model to the data was examined using the comparative fit index (CFI), normal fit index (NFI), root-mean-squared error of approximation (RMSEA), and standardized root mean residual (SRMR).

Results: There were 158 PwMS included in the analysis. The final model demonstrated that SDMT ($\beta = 0.16$), EDSS ($\beta = -0.33$), and HADS-D ($\beta = -0.23$) significantly predicted vocational status (*ps* < 0.05). It explained 37% of the variance and provided a good fit to the data ($\chi^2(11) = 13.01$, $p > 0.05$, SRMR = 0.055, RMSEA = 0.034, NFI = 0.94, CFI = 0.99.

Conclusions: Physical disability, depressive symptoms, and reduced information processing affect work-related disability and vocational status among PwMS. Interventions targeting these factors should be prioritized by clinicians.

1. Introduction

Multiple Sclerosis (MS) is a demyelinating disease of the central nervous system associated with varying physical disability, psychosocial symptoms, and cognitive impairment. As such, MS exerts a strong influence on a person's quality of life (QOL), specifically on their ability to work and remain employed (Benedict et al., 2005; Morrow et al., 2010a; Pack et al., 2014; Putzki et al., 2009). Previous research confirms that persons with multiple sclerosis (PwMS) are less likely to be employed, have reduced working hours, and retire at an earlier age compared to the general population (Moore et al., 2013; Pearson et al., 2017; Roessler et al., 2015; Simmons et al., 2010). Thus, finding clinically relevant predictors of vocational status is of upmost importance such that symptom management strategies and workplace accommodations can be instated for those at an increased risk of employment loss (Bishop and Rumrill, 2015; Bøe Lunde et al., 2014; Julian et al., 2008; Pack et al., 2014).

Prior research has uncovered a number of factors that are strongly correlated with employment in PwMS, such as disease course (i.e. progressive vs. relapsing-remitting MS) (Busche et al., 2003; Gerhard et al., 2018; Grønning et al., 1990), neurological disability and cognitive symptoms (Cadden and Arnett, 2015; Krause et al., 2013;

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Strober et al., 2012). However, the majority of the research findings thus far do not clarify the independent contribution of these factors on employment in PwMS, which is problematic as many of these factors often overlap (e.g., depression and anxiety; Gill et al., 2019).

In this study, our objective was to identify independent predictors of vocational status in PwMS. To do so, we examined the independent contribution of cognitive, physical, and emotional factors associated with vocational status in PwMS using a structural equation modeling (SEM) approach.

2. Materials and methods

2.1. Participants

2.1.1. Inclusion Criteria

The present study was a retrospective chart review of PwMS seen at an academic tertiary care hospital in London, Ontario between July 2011 and April 2017. Demographics, vocational status, and measurements were all taken concurrently at a single timepoint within this observation window. Subjects were included in the study if they met all of the following conditions: had a confirmed diagnosis of MS based on the 2010 McDonald criteria (Polman et al., 2011); had an Expanded Disability Severity Scale (EDSS) rating of 0–7.0; were fluent in English; had received at a minimum a ninth-grade education; and who had completed all the measures detailed below.

2.1.2. Exclusion criteria

Patients were excluded from being a part of the study if any of the following restrictions applied; had received corticosteroids or had a confirmed MS relapse less than thirty days before cognitive testing; were diagnosed with a psychiatric or secondary neurological disease with the potential to affect cognitive function; were listed as a stay at home parent or student; had reported ongoing drug abuse, specifically daily use of marijuana. Potential subjects with missing data were also excluded.

2.1.3. Demographics

Clinical charts were reviewed to collect the following information: demographics (age, gender, education, vocational status, history of psychiatric diagnosis) and MS specific factors (disease duration, MS course, date of most recent relapse).

2.1.4. Vocational status

Vocational status was broken down into seven categories: unemployed with objective disability, qualifies for disability benefits; unemployed with subjective disability, does not qualify for disability benefits; unemployed with no disability; employed part time, 10–20 h per week; employed full time with reduced capacity; and employed full time. As noted above, stay-at-home parent or students were excluded.

2.2. Measures

Expanded Disability Status Scale (EDSS) (Kurtzke, 1983). EDSS, a measure of disability, was measured by a trained MS neurologist. Scores range on an ordinal scale from 0.0 to 10.0 with a higher score indicating greater disability.

Fatigue Severity Scale (Krupp et al., 1989). Fatigue severity was measured by the nine-item Fatigue Severity Scale (FSS). Each item is rated on a 7-point Likert scale (“strongly disagree” to “strongly agree”) with a higher score indicating greater fatigue severity. The total score is divided by 9; the final score ranges from 0.0 to 7.0.

Symbol Digit Modalities Test (Rao, 1991). Processing speed was assessed by Rao's oral version of the Symbol Digit Modalities Test (SDMT). This cognitive measure consists of arbitrary symbols ascribed to numbers, and rows of randomized symbols for which examinees must orally respond the correct number assigned to each symbol in 90 seconds. Scores are calculated based on the number of correct symbol-digit pairings with higher scores indicative of better processing speed. The SDMT has been demonstrated to be a reliable measure for cognitive performance in PwMS (Benedict et al., 2017; Morrow et al., 2010b).

Hospital Anxiety and Depression Scale (Zigmond and Snaith, 1983). Anxiety and depressive symptoms were measured by the Hospital Anxiety and Depression Scale (HADS). The questionnaire consists of 14 questions scored on an ordinal scale from 0 to 3 with higher ratings indicating more severe symptoms. Half of the questions are anxiety specific (HADS-A subscale), while the other half measure depression severity (HADS-D subscale). The measure produces a score out of 21 that is separate for both anxiety and depression. The HADS-D was specifically chosen as it has been shown to be a better predictor of functional outcomes in PwMS as compared to the Beck Depression Inventory Fast Screen (BDI-FS) (Hanna et al., 2017).

Nine Hole Peg Test Dominant and Nondominant Hand (Feys et al., 2017). Fine motor function was tested using the Nine Hole Peg Test, Dominant and Non-dominant (NHPT-D/ND). The measure requires subjects to individually move nine small pegs into holes on a board and then remove them one at a time using only one hand. Two timed trials are completed for both the subject's dominant and non-dominant hands, and the average time of each hand is taken to produce a score. Low scores indicate better fine motor function and manual dexterity.

2.3. Statistical analysis

Descriptive statistics to summarize the demographic data was conducted using SPSS v23.0. Pearson's correlation was conducted to examine the relationship between vocation status and demographic, clinical, and psychosocial variables. Factors meeting threshold of $r > 0.1$ were incorporated into an exploratory structural equation model (SEM). SEM was developed to examine the predictive utility of clinical and psychosocial variables on vocational status after controlling for demographic and disease characteristics using AMOS SPSS v23.0. Based on guideline recommendations, several fit indices were used to assess model fit (Hooper et al., 2008). The overall model fit was assessed through the χ^2 statistic. The χ^2 test assesses the ‘magnitude of discrepancy between the sample and fitted covariances matrices (Hu and Bentler, 1995). The absolute misfit indices represent the robust root mean square error of approximation (robust RMSEA) (Browne and Cudeck, 1992). The RMSEA provides information on how well the model would fit the population's covariance matrix. It is an informative fit index because it is sensitive to the number of estimated parameters in the model. The RMSEA favors the model with lesser parameters (Hooper et al., 2008). The standardized root mean square residual (SRMR) is an absolute measure of fit. It is defined as the standardized difference between the observed correlation and the predicted correlation. A value of 0 on an SRMR is indicative of perfect fit; values as high as 0.08 are considered acceptable (Hu and Bentler, 1999) The Normed Fit Index (NFI) is a statistic that compares the χ^2 of the model to that of the null model. The null model is one that specifies that all variables are uncorrelated (Hooper et al. 2008). The Robust Comparative Fit Index (Robust CFI) was used to compute the relative goodness-of-fit index (Bentler, 1990). The CFI compares the fit of the model to the fit of null model. It is different from the NFI in that it takes into account sample size (Tabachnick and Fidell, 2007). As recommended by Hu and Bentler, a model with an acceptable fit to the data should have a robust RMSEA of < 0.08 and a robust CFI and NFI of > 0.9 (Hu and Bentler, 1995). A statistical significance level of 5% was set for the estimated paths in the proposed model.

This study was granted approval by the Western University Health Sciences Research Ethics Board.

Table 1
Descriptive statistics of participant demographics and MS characteristics.

Variable	Mean	Standard deviation	Median	Range
Age (years)	43.06	9.96	-	-
Education (years)	14.09	2.24	-	-
Gender	-	-	-	-
MS duration (years)	7.82	7.81	-	-
MS course	-	-	-	-
EDSS	-	-	2	0–7
FSS	4.13	1.6	-	-
SDMT	54.06	13.01	-	-
HAD-A	7.62	3.61	-	-
HAD-D	4.66	3.56	-	-
NHPT-D	23.93	19.1	-	-
NHPT-ND	25.47	20.14	-	-
Vocation	-	-	7	1–7

EDSS: expanded disability status scale; FSS: fatigue severity scale; SDMT: symbol digit modalities test; HAD-A: hospital anxiety scale; HAD-D: hospital depression scale; NHPT-D: nine hole peg test dominant hand; NHPT-ND: nine hole peg test nondominant hand.

3. Results

3.1. Subjects

In total, there were 158 PwMS who met the inclusion criteria and were included in the analysis. The cohort consisted of individuals with a mean age of 43.1 years ($SD = 10$) and consisted of 65.2% females. The majority of subjects, 65.8%, had full-time employment, while having completed an average of 14.1 years ($SD = 2.2$) of formal education. In regard to their MS, 81.0% of subjects had a relapsing remitting disease course, and the mean disease duration was 7.8 ($SD = 7.8$) years. The median EDSS was 2.0 (0–7.0) (Table 1).

3.2. SEM analysis

First, correlations between variables were explored (Table 2). Due to the exploratory nature of the study, factors with an association $r > 0.1$ with vocational status were included in the initial model (Figure 1). The initial structural equation model did not result in good fit $\chi^2(19) = 39.32$, $p = 0.004$, CFI = 0.94, NFI = 0.90, RMSEA = 0.083; SRMR = 0.099. In this model, FSS, SDMT, EDSS, NHPT, HADS-D, and HADS-A were added as predictor variables for vocational status. Covariates included age, sex, education, MS course, and MS duration. No significant associations were found between vocational status and FSS, NHPT, and HADS-A.

A second model was developed by removing non-significant factors and only retaining, as covariates, those that resulted in significant associations with vocational status, specifically: SDMT, EDSS, HADS-D; age, sex, education, MS course, and MS duration. This second structural equation model demonstrated good fit to the data $\chi^2(11) = 13.01$, $p = 0.292$, CFI = 0.99, NFI = 0.94, RMSEA = 0.034; SRMR = 0.055 (Figure 2). In this model, vocational status was shown to have a positive association with SDMT ($\beta = 0.16$, $p < 0.05$); while a negative association was found with EDSS ($\beta = -.33$, $p < 0.05$) and HADS-D ($\beta = -.23$, $p < 0.05$). The final model explained 37% of the variance.

4. Discussion

Decreased processing speed and increased disability and depression were found to be independent predictors of vocational status in PwMS that significantly predicted employment. To establish independent predictors of vocational status in PwMS, an exploratory SEM approach was used to examine clinical and psychosocial factors. Upon determining that processing speed, disability, and depressive symptoms were significant factors in predicting employment status, our final model demonstrated that these three factors explained 37% of the variance in employment, while controlling for age, sex, disease course, education, and disease duration. Furthermore, fatigue, fine motor control, and anxiety symptoms were not found to be significant predictors of vocational status in our model.

To the best of our knowledge, this investigation is the first to use a SEM approach to identify independent predictors of vocational status in PwMS, we do not have other models to compare our results. However, the benefit to utilizing SEM in this study was that it allowed us to control for covariates known to have a functional impact on PwMS and simultaneously allowed us to adjust for the interrelation among variables of interest. Moreover, when compared to other studies with different methodologies and statistical techniques, our findings align quite well. In particular, recent work has demonstrated that neurological disability (Bøe Lunde et al., 2014; Krause et al., 2013; Lorefice et al., 2018) and declining information processing speed (Campbell et al., 2017; Honan et al., 2015; Morrow et al., 2010a; Strober et al., 2014) significantly predict unemployment in PwMS.

In our investigation, we also found that depression symptoms were significant in determining one's employment status, which is consistent with research showing the depression in PwMS coincides with reduced working hours (Honan et al., 2015) and is predictive of unemployment in univariate (Forslin et al., 2018) and multivariate models (Honarmand et al., 2011). However, a number of other studies have demonstrated that depression does not have an independent effect on employment (Bøe Lunde et al., 2014; Cadden and Arnett, 2015; Lorefice et al., 2018; Patten et al., 2013).

Table 2
Correlations between participants demographics and MS characteristics.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age (years)	—	-0.05	0.05	0.57*	0.57*	0.39*	0.31*	-0.25*	0.21*	.026*	0.11	0.05	−0.44*
2. Education (years)	−0.05	—	0.14	−0.08	−0.04	−0.12	−0.16*	0.07	−0.14	−0.09	0.02	0.03	0.15
3. Gender	0.05	0.14	—	0.06	0.04	−0.05	0.01	0.18	0.12	0	0.03	0.12	0
4. MS duration (years)	0.57*	−0.08	0.06	—	0.51	0.37*	0.21*	−0.14	0.21*	0.21*	0.22*	0.09	−0.32*
5. MS course	0.57*	−0.04	0.04	0.51*	—	0.61	0.26*	−0.24*	0.08	0.17*	0.35*	0.29*	−0.51*
6. EDSS	0.39*	−0.05	-0.12	0.37*	0.61*	—	0.29*	−0.26*	0.12	0.28*	0.41*	0.36*	−0.51*
7. FSS	0.31*	−0.16*	0.01	0.21*	0.26*	0.29*	—	−0.15	0.47*	0.55*	0.06	0	−0.31*
8. SDMT	−0.25*	0.08	0.18	−0.14	−0.24*	−0.26*	−0.15	—	−0.08	−0.08	−0.03	−0.22*	0.1
9. HAD-A	0.21*	-0.14	0.12	0.21*	0.08	0.12	0.47*	−0.08	—	0.57*	0.17	−0.03	−0.19*
10. HAD-D	0.26*	−0.09	0	0.21*	0.17*	0.28*	0.55*	−0.08	0.57*	—	0.16	0.01	−0.39*
11. NHPT-D	0.11	0.03	0.02	0.22*	0.35*	0.41*	0.06	−0.03	0.17	0.16	—	0.08	−0.27*
12. NHPT-ND	0.05	0.03	−0.12	0.09	0.29*	0.36*	0	−0.22*	-0.03	0.01	0.08	—	−0.21*
13. Vocation	−0.44*	0.15	0	−0.32*	−0.51*	−0.51*	−0.31*	0.1	−0.19*	−0.39*	−0.27*	−0.21*	—

EDSS: expanded disability status scale; FSS: fatigue severity scale; SDMT: symbol digit modalities test; HAD-A: hospital anxiety scale; HAD-D: hospital depression scale; NHPT-D: nine hole peg test dominant hand; NHPT-ND: nine hole peg test nondominant hand.

* $p = 0.05$.

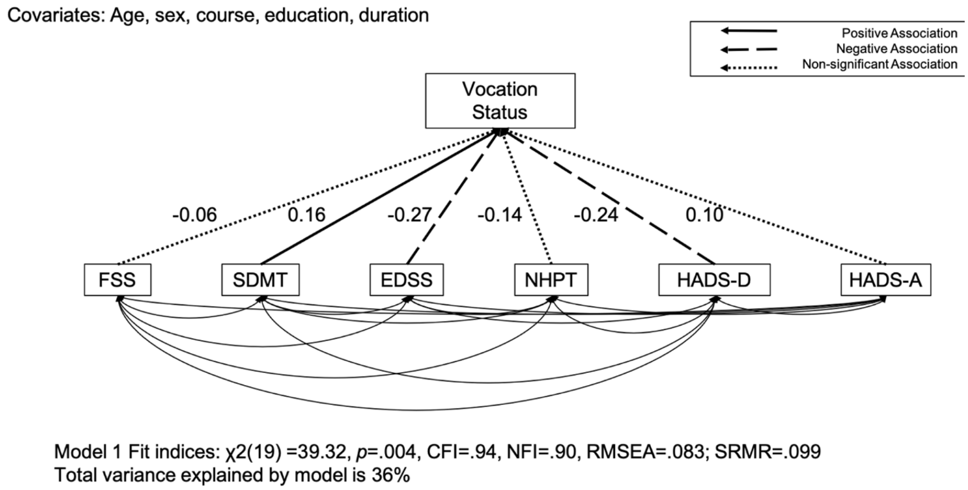

Fig. 1. Initial SEM model.

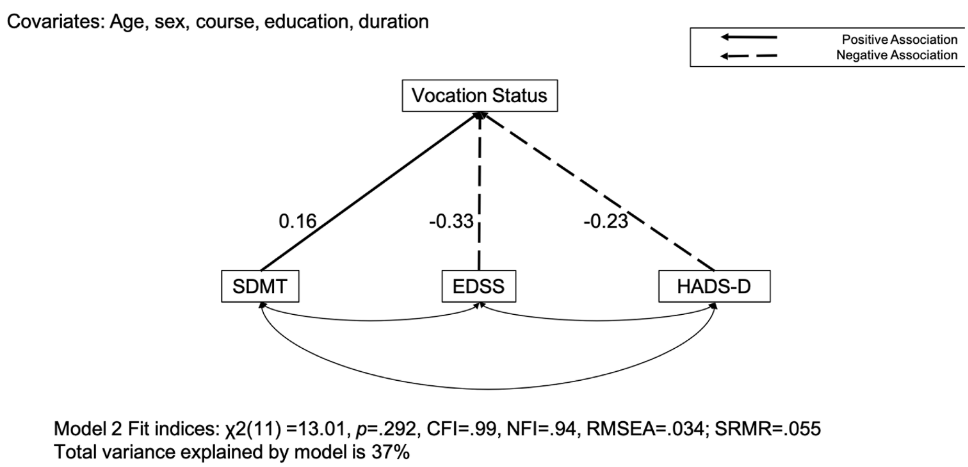

Fig. 2. Final SEM model including only significant factors.

The causality and significance of depression on vocational status for PwMS is yet to be agreed upon, likely due, in part, to the lack of a universal depression standard and because of its' complex relationship with other variables such as cognitive function, disability, and fatigue. Previous research has employed a variety of methods to measure depression leading to inconstancies in reported and actual depression incidence. Evidence showing that the HADS-D is more effective than the BDI-FS at predicting functional outcomes in PwMS (Hanna et al., 2017) is a testament to the fact that different measures of depression are not equal. In addition, depression can be conceptualized as a result of functional transitions in MS, mediated by new or worsening symptoms, and therefore should be thought of as only an indicator of these transitions and not an independent factor (Patten et al., 2013). Physical disability, cognitive function, and fatigue may further increase the risk of depression resulting in a complex relationship with these common MS sequalae (Arnett et al., 2008). In fact, prior research has shown depression to be significantly correlated with fatigue, cognition, and disability, however no single variable was able to completely mediate its' effect on functional outcomes (Gill et al., 2019). Due to the mediating effects and associations with other MS related symptoms, it is difficult to determine whether depression itself is causal to employment status or arises as a result of a functional transition in disease course.

Similarly, the research community has not always agreed upon the role fatigue plays in PwMS transitioning to unemployment. Several studies indicate that increased fatigue predicts unemployment (Bøe Lunde et al., 2014; Cadden and Arnett, 2015; Krause et al., 2013). In contrast, a recent ten-year longitudinal study showed that increased fatigue predicted full or part-time work as opposed to being unemployed (Forslin et al., 2018). This may be explained by the idea that remaining employed increases one's responsibilities and subsequent work load, thereby intensifying fatigue symptoms. Other studies, including our own, showed that fatigue is not a significant predictor of employment status (Lorefice et al., 2018; Strober et al., 2012). Given these dissenting results we cannot definitively conclude that fatigue is not a significant predictor of vocational status; the exact relationship between fatigue and unemployment requires further study.

There are several limitations to our study. To begin, our study is retrospective and cross-sectional in nature, thus we cannot assume causal relationships between the variables investigated and vocational status. Second, our study sample was taken from a hospital-based outpatient clinic where the severity of MS may be greater and over-represented in this group. While this study looked at some of the most pertinent and well documented predictors of employment in MS, we neglected to take into consideration workplace factors that may affect the transition to unemployment. Environmental and social factors such as flexible work hours, accessible spaces, supportive employers, and lack of discrimination are reported as helping to retain employment (Chandraratna, 2010). Moreover, barriers such as inflexible work schedules, lack of social supports in the workplace, and financial insecurity correlate with increased unemployment (Johhson et al., 2004; Messmer Uccelli et al., 2009). Environmental and social barriers should be accounted for when implementing vocational rehabilitation strategies (Frain et al., 2015; Roessler et al., 2004), and we suggest future research incorporate these factors when predicting employment status in PwMS. As the SEM is limited to evaluating linear relationships among the specific variables, further analysis using nonlinear models may be warranted. Lastly, while the SDMT serves as a robust measure for processing speed, it does not encompass all facets of cognitive function which may be important for examining vocational status changes (Ruet et al., 2013). We suggest incorporating more cognitive testing measures such as those which assess executive functioning, as these have been used previously to evaluate vocational status in PwMS (Benedict et al., 2005; Covey et al., 2012).

5. Conclusion

In conclusion, this study demonstrates that neurological disability, reduced information processing speed, and depressive symptoms are independent predictors of vocational status in PwMS, and when combined, explained 37% of the employment variance in our study sample. These clinically relevant predictors for unemployment should be used to inform clinical care in PwMS so that early intervention strategies can be implemented to reduce job loss and prolong employment.

Declaration of Competing Interest

Sarah A. Morrow has, in the past 3 years, served on advisory boards for Biogen Idec, EMD Serono, SanofiGenzyme Canada, Novartis, Roche; has received Investigator Initiated Grant Funds from Biogen Idec, Novartis, Roche; has acted as site PI for multi-center trials funded by Novartis, Genzyme, Roche, Adamas and AbbVie.

There are no other conflicts to report for any author.

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