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Two Methods for Calculating Symptom Cluster Scores

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Abstract

Background: Symptom clusters are conventionally distilled into a single score using composite scoring which is based on the mathematical assumption that all symptoms are equivalently related to outcomes of interest; this may lead to a loss of important variation in the data.

Objectives: This paper compares two ways of calculating a single score for a symptom cluster: A conventional, hypothesis-driven composite score versus a data-driven, reduced rank regression score that weights the symptoms based on their individual relationships with key outcomes.

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Methods: We conducted a secondary analysis of psychoneurological symptoms from a sample of 356 low-income mothers. Four of the psychoneurological symptoms (fatigue, cognitive dysfunction, sleep disturbance, and depressed mood) were measured with the Center for Epidemiological Studies Depression Scale; the fifth (pain) was measured using an item from the Medical Outcomes Study 12-item Short Form Health Survey (SF-12). Mothers' function was measured using the SF-12. The composite score was calculated by summing standardized scores for each individual psychoneurological symptom. In contrast, reduced rank regression weighted the individual symptoms using their respective associations with mothers' function; the weighted individual symptom scores were summed into the reduced rank regression symptom score.

Results: The composite score and reduced rank regression score were highly correlated at 0.93. The cluster of psychoneurological symptoms accounted for 53.7% of the variation in the mothers' function. Depressed mood and pain accounted for almost all the explained variation in mothers' function at 37.2% and 15.0%, respectively.

Discussion: The composite score approach was simpler to calculate, and the high correlation with the reduced rank regression score indicates that the composite score reflected most of the variation explained by the reduced rank regression approach in this dataset. However, the reduced rank regression analysis provided additional information by identifying pain and depressed mood as having the strongest association with a mother's function, which has implications for understanding which symptoms to target in future interventions. Future studies should also explore composite versus reduced rank regression approaches given that reduced rank regression may yield different insights in other datasets.

Keywords

maternal health; psychoneurological symptoms; reduced rank regression; symptom clusters

Nurse researchers have identified the reduction of intrusive symptoms as a core component of nursing practice (Cashion, Gill, Hawes, Henderson, & Saligan, 2016), with the National Institute of Nursing Research (NINR) calling for an increase in symptom science research (Cashion & Grady, 2015). While symptoms can be researched individually, evidence is accumulating that some symptoms frequently appear together: A phenomenon known as a symptom cluster. A symptom cluster can be defined as two (or more) symptoms occurring at the same time; additionally, a symptom cluster occurs independently and the symptoms included may have shared underlying mechanisms and/or outcomes (Miaskowski et al., 2017).

There are benefits in researching symptoms as a cluster, rather than individually. Clusters seem to be associated with worse patient outcomes than single symptoms (Miaskowski et al., 2017), and interventions for one symptom may affect the levels of the other symptoms in the cluster (Miaskowski et al., 2017). Along these lines, an expert panel published a review on the state of symptom cluster science and identified key areas for consideration (Miaskowski et al., 2017). This paper will address two of those key areas—measurement issues and new analytic strategies—by testing a new strategy for measuring a symptom cluster as a single score. This is an important undertaking as we must be able to accurately

calculate symptom cluster scores in order to investigate the relationships between clusters and other important variables.

Symptom Clusters

A variety of techniques to identify symptom clusters within a dataset have been used in past research in this area. In their state of the science review, Miaskowski and colleagues (2017) discuss the use of de novo techniques (e.g., factor analysis, hierarchical cluster analysis, principal components analysis) which are useful when researchers are seeking to identify novel clusters. The review also discusses a priori techniques (e.g., hierarchical cluster analysis, latent class analysis), which are used to determine the presence of prespecified symptom clusters (Miaskowski et al., 2017). However, very little attention has been paid to how to create a single score once the symptom cluster has been identified within the dataset —regardless of whether the researchers have used de novo or a priori clustering methods. The distillation of the symptom cluster into a single score is a crucial step, as this score will dictate how the symptom cluster appears to associate with other variables; our paper advances the science in this area.

One simple technique that has been used to create a single score from a symptom cluster is the calculation of a composite symptom score (Starkweather et al., 2013). A benefit of using this technique is that it is relatively simple, making symptom cluster research more accessible to researchers without advanced quantitative training. Though, in creating a composite score, each symptom is given equal weight (Starkweather et al., 2013), making the mathematical assumption that each symptom carries equal importance with respect to the associated outcome(s) of interest. In other words, individual symptoms of fatigue and pain may cluster together, but pain may be a stronger predictor of day-to-day functioning than fatigue; a fact that would be obscured by creating a composite score of fatigue and pain and looking at its association with functioning.

Alternatively, a symptom score could be created by using other information from a dataset to weight different symptoms within the cluster, based on their associations with outcomes. One analytic method available to accomplish this is reduced rank regression (RRR), which, like composite scores, can also create a single symptom score from of a cluster of individual symptoms. RRR is a statistical technique that can also be used to identify the patterns within a set of correlated predictors that tend to be associated with one or more outcomes (Izenman, 1975; Jaacks et al., 2015). RRR aims to explain as much of the variation in a set of responses (outcomes) as possible from the set of predictors. Specifically, it creates a factor (i.e., linear combination) from the set of predictors that is the most predictive of variations in the set of responses (Hoffmann, Schulze, Schienkiewitz, Nöthlings, & Boeing, 2004). It can be helpful to think of RRR as an extension of exploratory factor analysis (EFA). In EFA, the first factor is a linear combination of a single set of variables that collectively explains the most variation in those variables. In RRR, the first “factor” (commonly called “pattern” in the RRR literature) is the linear combination of the first set of variables (predictors) that explains the most variation in a *second* set of variables (outcomes).

The RRR approach uses data from the study itself to create a score, making it an a posteriori or data-driven method (Hoffmann et al., 2004). RRR has been most commonly used in dietary data, where a set of correlated nutrient intake variables are used as predictors of health outcomes (Hoffmann et al., 2004). RRR has also been used in studying nutrition epidemiology to identify associations between dietary intake patterns and many outcomes of wellness and disease (e.g., Jaacks et al., 2015; Lamichhane et al., 2014). To our knowledge, RRR has not yet been used in the calculation of a single score from symptoms in a symptom cluster. RRR has potential for symptom science because it can identify the pattern of symptoms that explains the most variation in specific outcomes. In doing so, RRR could generate unique knowledge regarding which symptoms within a cluster are most important to assess—and intervene upon—given their associations with other important variables.

Psychoneurological Symptoms in Low-Income Mothers

In this paper, we use the psychoneurological symptom cluster (composed of pain, fatigue, cognitive dysfunction, sleep disturbance, and depressed mood) as an example to test the utility of composite and RRR metrics. Nurse researchers first identified this cluster in women with breast cancer (Kim, Barsevick, Tulman, & McDermott, 2008) and fibromyalgia (Menzies, Lyon, Elswick, Montpetit, & McCain, 2013), and it has continued to be a main symptom cluster of interest across different chronic conditions (Miaskowski et al., 2017). Typically, when symptom researchers are interested in chronic conditions, they mean chronic disease states. However, we contend that chronic environmental conditions, including socioeconomic environment, can also induce symptomatology, as evidenced by the accumulation of research on chronic stress as a significant social determinant of health (Braveman, Egerter, & Williams, 2011). In fact, even within research on chronic diseases, the psychoneurological symptom cluster has been associated with perceived stress (Kim & Malone, 2019; McCain, Gray, Walter, & Robins, 2005). Building on past research that has examined psychoneurological symptom cluster in the context of chronic disease conditions, here we examine psychoneurological symptom cluster in the context of the stressful chronic environmental condition of parenting with low income.

Low-income mothers are a vulnerable population under high amounts of chronic stress (Baum, Garofalo, & Yali, 1999; Luthar & Ciciolla, 2016). Chronic stressors are classified as situations that are demanding, distressing, and ongoing and come in a variety of types, including neighborhood environment, financial strain, interpersonal stress, work stress, and caregiving (Epel et al., 2018). Low-income mothers often face many of these chronic stressors in tandem (Beeber, Perreira, & Schwartz, 2008), which may cause them to experience psychoneurological symptoms, but the presence of the symptom cluster in this population has not been investigated.

With the exception of pain, the symptoms in the psychoneurological symptom cluster could also be considered depressive symptoms. Depressive symptoms in mothers, and possible effects on their children, have been studied for many years (Downey & Coyne, 1990; Gross, 1989; Hammen et al., 1987). In low-income mothers, interventions to alleviate depressive symptoms have had variable levels of efficacy (Appleby, Warner, Whitton, & Faragher, 1997; Beeber & Miles, 2003; Forman et al., 2007; Miranda et al., 2006). The limited

efficacy may be because interventions addressing depressive symptoms often do not target pain, which was experienced by 50% of low-income mothers in one study (Kneipp et al., 2011). Additionally, some mothers have communicated their symptoms as reactions to stress and resisted the term “depression” (Beeber et al., 2007). Focusing future interventions on psychoneurological symptoms rather than depressive symptoms decouples the symptoms from the stigma of mental illness; a major barrier to intervention in this population (Miranda et al., 2006).

Mothers’ Function

In order to complete the RRR analysis and create a symptom cluster score, researchers must identify an “outcome” of interest within the dataset that is used to weight each individual symptom in the final cluster value. One way to select a variable is to draw from a conceptual framework. The Symptoms Experience model constructs a person’s symptom experience through the antecedents of symptoms, the perception of symptoms, and the consequences of symptoms (Armstrong, 2003). Specifically, this framework argues that, when one or more symptoms are perceived by an individual, the expression of the symptoms has direct effects on a variety of outcomes, including functional status (Armstrong, 2003). Psychoneurological symptoms are known to have negative effects on function in other populations, such as women with breast cancer (Dodd, Cho, Cooper, & Miaskowski, 2010). Further, a mother’s ability to function not only affects her own life, but can also affect her children (Gross, 1989). Past research has shown that depressive symptoms are related to compromised function in mothers during the infancy and early childhood periods (Trapolini, Ungerer, & McMahon, 2008; Warnock, Craig, Bakeman, Castral, & Mirlashari, 2016). Thus, we felt the mother’s function was an important variable to consider when testing the usefulness of RRR analysis.

Purpose

The purpose of this paper is to compare two ways of distilling the psychoneurological symptom cluster into a single score: The composite score approach versus the RRR approach, which weights the individual symptoms in the cluster based on their association with an outcome measure. For the RRR score, the predictors of interest are mothers’ psychoneurological symptoms (i.e., pain, fatigue, cognitive dysfunction, sleep disturbance, depressed mood); these symptoms were identified a priori from the literature (e.g., Kim et al., 2008; Menzies et al., 2013; Starkweather et al., 2013). The main outcome of interest is the mother’s function. In addition to indicating function as a key outcome related to symptom experience, the Symptom Experience model states that, when multiple symptoms occur together, those symptoms influence each other and are “likely to result in an experience that is multiplicative rather than additive” (p. 603, Armstrong, 2003). This suggests that a composite scoring approach may not adequately reflect the complexity of symptom clusters. To our knowledge, this article is the first to consider the potential of RRR for identifying symptom patterns associated with key variables; thus, advancing the statistical methods available for symptom science research.

Methods

Sample

The sample for this study comprised 356 low-income mothers drawn from two studies conducted in New York and North Carolina (Beeber et al., 2010, 2013). The two parent studies, HILDA (R01 MH065524; Beeber, PI) and ALAS(R34 MH086553; Beeber, PI) were longitudinal intervention projects. However, the current study used the prerandomization, pre-intervention baseline data from both parent studies. Mothers who were eligible for participation in the original interventions had mild to severe depressive symptom severity scores; this study also included a subset of mothers with no depressive symptoms whose data were collected as part of the HILDA study. No additional inclusion or exclusion criteria were applied for the secondary analysis. This research was approved by the institutional review board at the University of North Carolina at Chapel Hill. Further details on the study sample are available in the Appendix.

The available sample size for this study was 356 (251 from HILDA and 105 from ALAS). When calculating the composite score, three participants had missing data for individual symptoms and were removed, leaving a final sample of 353. For the RRR analysis, 333 mothers were included after those with missing data were removed. The reason for the difference in subjects (333 vs. 353) across analytic approaches is that more subjects were missing data on the functional outcomes of interest—which are required to compute the RRR—than were missing data on the individual symptoms. Information on power calculations is available in the Supplemental Data File

Measures

Each of the five individual psychoneurological symptoms was measured using items collected during the parent studies. Non-English-speaking Latina mothers were given Spanish versions of the Center for Epidemiological Studies Depression Scale (CES-D) as well as the Medical Outcomes Study 12-item Short Form Health Survey (SF-12; Beeber et al., 2010). These questionnaires had previously demonstrated reliability and validity with Spanish-speaking populations, and, to ensure clarity, mothers from Early Head Start programs who were similar to the expected sample reviewed the questionnaires prior to data collection (Beeber et al., 2010).

To measure fatigue, cognitive dysfunction, sleep disturbance, and depressed mood, we deconstructed the CES-D, as shown in Table 1 (Radloff, 1977). We borrowed the idea to deconstruct the scale from the researchers who developed the revised CES-D (Eaton, Smith, Ybarra, Muntaner, & Tien, 2004). Eaton and colleagues (2004) have shared details on which items from the revision can be used to score specific symptoms, including fatigue, thinking/concentration difficulties (i.e., cognitive dysfunction), and sleep disturbance. While there is not a one-to-one match between the revised CES-D and the original CES-D (which we had available for analysis), many of the items are identical across the two versions of the scale. When the same items were available, we flagged those as corresponding to the symptoms of interest (see Table 1). This direct comparison accounted for six out of the 12 items we included. The additional six items were added based on expert input (from the three

psychiatric nurse researchers who are authors on this paper) with additional support from the literature.

All item prompts are listed in Table 1. Fatigue was measured as severity of behavioral manifestation of fatigue over the past two weeks. The measure of cognitive dysfunction included one item related to perceived cognitive impairments and a second related to psychomotor retardation. Psychomotor retardation has been included in previous measures of cognitive dysfunction in psychoneurological symptom cluster research (Starkweather et al., 2017); verbal frequency has been used as a measure of psychomotor function and mental flexibility (Thomas-Ollivier et al., 2017). Sleep disturbance was measured as restlessness while sleeping over the past two weeks. After removing the items regarding fatigue, cognitive dysfunction, and sleep disturbance, we created the depressed mood symptom score by summing the scores of the remaining nonsomatic items on the CES-D. Depressed mood included items related to both loss of interest (anhedonia) and sadness (dysphoria) (Eaton et al., 2004).

The internal reliability for all the items used from the CES-D was alpha = .901, which was very close to the reliability for the whole measure (alpha = .927). Internal reliability remained high for the depressed mood symptom (alpha = .892) but was lower for fatigue (alpha = .435) and cognitive dysfunction (alpha = .556). These lower reliabilities were expected, as each was represented by only two items. Internal reliability could not be calculated for sleep disturbance as it contained only one item.

Pain was measured as pain interference using the Medical Outcomes Study 12-item Short Form Health Survey (SF-12; Ware, Kosinski, & Keller, 1996), item 5 (see Table 1 for prompt). Pain interference has been used as an indicator of pain in psychoneurological symptom research and has significant correlations with pain severity (Menzies et al., 2013).

Mother's function was constructed using the SF-12, which includes four subdomains of function: physical functioning, social functioning, role functioning (physical), and role functioning (emotional) (Ware et al., 1996). Internal reliability for the items was alpha = .84.

Statistical Analysis

First, we used a simple approach to calculate a composite symptom score (MacCallum, Widaman, Zhang, & Hong, 1999). Sleep disturbance was measured on a 0–3 scale, so all the other symptoms were standardized to be on the same scale for the purpose of computing the composite score. The standardized individual symptom scores were summed into a composite score, with higher scores indicating higher symptom intensity.

Second, we used RRR. Scale is irrelevant for RRR, as all variables are standardized to $M = 0$ and $SD = 1$ in the RRR procedure. Following procedures from prior research (Jaacks et al., 2015; Lamichhane et al., 2014), RRR was conducted using the partial least squares procedure in SAS software specifying method = RRR (version 9.4; SAS Institute, Cary, NC). The SAS code is available in the Supplemental Digital File.

This procedure calculated the linear combination of psychoneurological symptoms that was most predictive of mothers' function. While we were only ultimately interested in a single

factor (i.e., the combination of individual symptoms), we set the number of factors to extract to 5 (nfac = 5) so that we could review any other factors produced. The linear combination was then used to generate the symptom score that was most predictive of the set of responses (i.e., the function variables). In other words, in contrast with the literature-based approach, the RRR approach does not give equal weight to each symptom but rather identifies weights that yield the strongest association with the mother's function. The derived weights were applied to the individual symptoms and summed into the RRR symptom score.

Finally, we assessed the correlation between the two scores to determine whether there was a marked difference in the way the symptom cluster was summarized between the composite symptom score and the RRR symptom score. It was determined a priori that if the composite score explained more than 80% of the variance in the RRR symptom score—as identified by a correlation coefficient greater than $\sqrt{.80}$ = .89—the composite score would be deemed sufficient for any future analyses with this dataset.

Results

In the combined dataset, mothers had a mean age of 26, had completed an average of 11 school years, and almost half (46%) lived without a partner. The mean baseline CES-D scores for the combined sample was 23 (min/max = 0 to 55 out of a possible score range of 0 to 60; *SD* = 14). The combined sample was thus 41% Black (African American; non-Hispanic), 36% Hispanic/Latina, 16% White (Caucasian; non-Hispanic), and 7% Other.

Symptom Scores

When calculating the composite score, each individual symptom score was scaled from 0 to 3 to ensure that all symptoms would be weighted equally. After scaling, the means and standard deviations of these individual symptom scores were: pain (*M* = 0.77, *SD* = 0.89); fatigue (*M* = 1.33, *SD* = 0.81); cognitive dysfunction (*M* = 1.19, *SD* = 0.87); sleep disturbance (*M* = 1.44, *SD* = 1.19); and depressed mood (*M* = 1.25, *SD* = 0.83). The mean composite score was 5.98 (*SD* = 3.47) with a range from 0 to 14.11 (out of 0 to 15).

The RRR summarized the symptom pattern that best explained mothers' functioning. Table 2 illustrates the association of each individual symptom (i.e., pain, fatigue, cognitive dysfunction, sleep disturbance, and depressed mood) with the RRR symptom score. The factor loadings and Pearson's correlations were all positive, indicating that all symptoms were positively associated with the RRR symptom score. The standardized score parameters are the weights used to compute the RRR symptom score from the standardized symptoms. The explained variation in score indicates the relative contribution of each symptom to the total RRR symptom score. The RRR also provided the association of each of the symptoms with mothers' functioning. The symptoms explained 53.7% of the total variation in the mothers' functioning, with depressed mood explaining 37.2%, pain explaining 15.0%, fatigue explaining 0.9%, cognitive dysfunction explaining 0.5%, and sleep disturbance explaining 0.1%.

Correlating the Composite and RRR Scores

After calculating the two symptom cluster scores (i.e., composite and RRR), our main analysis of interest was to examine the Pearson correlation between the two scores. We reasoned that, if the correlation between the two measures was sufficiently high (i.e., $r > .89$), then the parsimony of the composite score would be preferred over the more complex RRR score. However, if the two measures were not highly correlated, this would indicate that the two methods for calculating symptom cluster scores are providing sufficiently different information to warrant including both in models attempting to understand antecedents and outcomes of the symptom cluster. The Pearson correlation coefficient for the correlation between the composite symptom score and the RRR symptom score was 0.93 ($p < .001$), above the threshold of 0.89. The threshold of 0.89 is the R^2 of 0.8, which was determined by the authors a priori to represent 80% of the variability. This high level of correlation shows there was not a large difference between the composite symptom score and the RRR symptom score.

Discussion

In this paper, we compared two ways of distilling a symptom cluster into a single score: The conventional composite score versus an RRR score that calculates weights for the symptoms based on their individual relationships with key outcome variables. Conventional investigation of symptom clusters uses a composite symptom score that is based on the mathematical assumption that all symptoms are equivalently related to outcomes of interest —which may lead to a loss of important variation in the data. Alternatively, RRR is a more computationally intensive approach that could yield additional insight above and beyond a composite score. Here, we calculated psychoneurological symptom cluster scores using both methods, and evaluated the association between them to assess variation in the overall symptom scores produced by the two approaches.

Within this dataset, the composite score approach reflected the majority of the variation revealed by the RRR approach, as revealed by the high correlation between the two scoring approaches. Given that the composite score approach is more parsimonious and straightforward to calculate, these findings suggest that, in this dataset, a composite score is sufficient for summarizing psychoneurological symptoms. Nonetheless, the RRR analysis provided additional information that the simple composite score could not. The RRR analysis determined which of the symptoms (pain and depressed mood) were most closely associated with a mother's function and provided the necessary weights for creating the RRR score. Therefore, while the scoring methods did not provide quantitatively different results (as evidenced by their high association with one another), there was a descriptive value in calculating the RRR score that would not have been possible by calculating the composite score alone.

Symptom science researchers have advocated for the adoption of a consistent scoring method for symptom clusters, such as the composite score technique (Starkweather et al., 2013). As Starkweather and colleagues (2013) point out, using the composite score technique allows researchers to include interdependent symptoms in the cluster as well as multiple components of each symptom's experience, such as intensity, frequency, and

interference. However, there are risks in this simpler approach. The composite score is not data-driven and may lead to the inclusion of redundant symptoms or underemphasize the role of more important symptoms. In essence, it is possible that a composite score could mask how specific symptoms within a cluster are behaving in relation to important variables such as biological mechanisms or health outcomes.

RRR serves as a data-driven method to examine the appropriateness of the use of the composite score. In our dataset, the two scores were quite similar, with the RRR supporting the composite score as appropriate. In another dataset, the composite score and RRR may not be as highly correlated, which should prompt researchers to delve into what could account for those differences. In either case, using the RRR strengthens the science, by either validating or calling into question the composite symptom score.

As we have noted, the primary application of RRR has been the identification of dietary patterns (e.g., Hoffmann et al., 2004; Jaacks et al., 2015; Lamichhane et al., 2014). RRR was created for dimension reduction, or to take a vast number of predictors (such as hundreds of individual nutrients in a person's diet) to create a single score to use in other statistical analyses. Even without a vast number of predictors (for this study, only five were included), the RRR method provides novel utility in that it reduces the rank in connection with specific outcomes. Using the prior literature, we could identify that the psychoneurological symptoms were likely to be present and clustered in these mothers. Then, using RRR, we were able to investigate if each symptom was equally related to the mothers' functioning or if some symptoms were more important for that outcome than the others.

The weighted results from the RRR score identified pain and depressed mood (loss of interest, sadness) as having the strongest association with a mother's function. This suggests that, if researchers seek to develop interventions to improve the function of low-income mothers— in hopes of improving her quality of life and supporting the child's development —then they should include pain as a target of the intervention. As discussed previously, interventions targeted at maternal depressive symptoms have not included pain and have had mixed efficacy (Appleby et al., 1997; Beeber & Miles, 2003; Forman et al., 2007; Miranda et al., 2006). There is also a large literature on the development of parenting interventions. Many of those interventions target depressive symptoms but none directly address pain (National Academies of Sciences Engineering and Medicine, 2016; National Center for Parent, Family and Community Engagement, 2015), which may be a missed opportunity for improving maternal/child outcomes.

Still, concerns about pain while parenting are gaining attention. Prior research has demonstrated an association between pain and compromised function in mothers (Evans, Shipton, & Keenan, 2006, 2005). Findings also reveal that mothers with a history of more adverse childhood experiences—a potential chronic stressor—are more likely to experience chronic pain and that their children are more likely to report depressive symptoms (Dennis, Clohessy, Stone, Darnall, & Wilson, 2019). These researchers and others suggest the need for targeted interventions focused on parenting while experiencing pain (Dennis et al., 2019; Wilson & Fales, 2015). Our findings from the RRR analysis provide further support for this need.

Implications for Research

We assigned mothers' function as the variable of interest for weighting the RRR symptom score due to the Symptoms Experience model as well as the data available for analysis. But we could have used any number of other variables to weight the psychoneurological symptoms and create the RRR symptom score. This flexibility opens up a wealth of possibilities.

For example, if we had biological data available, we could have investigated how different symptoms within the cluster contributed to variability in potential underlying biological mechanisms. As previously explained, the composite score makes the mathematical assumption that all symptoms are contributing equally to the cluster, which might mask how specific symptoms within the cluster are associated with the biological mechanisms. The use of RRR analyses frees the researcher from such an assumption. Future research should investigate the relationship of the psychoneurological symptoms within the cluster to its proposed mechanisms: increased proinflammatory cytokines, alterations to the hypothalamic pituitary adrenal axis, and altered monoamine neurotransmission (Kim, Barsevick, Fang, & Miaskowski, 2012). In turn, this would reveal which biological mechanisms to target with interventions.

Limitations

Limitations of this analysis include the use of secondary data analysis as well as the potential for measurement error. While the secondary analysis allows researchers to make scientific contributions in an accelerated timeframe without increasing cost or incurring additional participant burden, this design also limits the researchers to the items that were collected. In the case of this study, symptoms were not assessed using more complete symptom measures that have been used in other work in this area (e.g., Starkweather et al., 2013). Instead, each individual psychoneurological symptom was measured with anywhere from one to seven self-reported items. Further, items from the CES-D were used for four out of the five symptoms of interest. Each issue may have introduced measurement error. Another limitation was that the selection of 80% as the threshold for correlation between the composite score and RRR score was chosen by the investigators as there is no established threshold in the literature; a higher or lower threshold may be appropriate and should be explored in future research. Despite these limitations, this study still provides interesting findings regarding the usefulness of a novel method for calculating symptom cluster scores.

Conclusion

In our dataset, the high correlation between symptoms scores calculated using RRR and standard composite methods suggests that the more parsimonious composite score may be sufficient for creating a single score from the psychoneurological symptoms within this dataset. Other researchers interested in summarizing a symptom cluster in their own datasets should consider validating the composite score using RRR. In addition to providing validation by weighting the symptoms based on their relationship with a set of outcomes, RRR provides information on the effect and importance of these individual symptoms. Given the call by the NINR for the development of interventions to alleviate symptoms,

RRR may provide researchers with key information on which symptoms to target within a symptom cluster in order to improve patient experiences.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Items used to construct each of the individual psychoneurological symptoms

Individual symptom	Scale	Item number	Prompt
Fatigue	CES-D	7[c]	I felt that everything I did was an effort.
		20[b]	I could not get “going.”
Cognitive dysfunction		5[b]	I had trouble keeping my mind on what I was doing.
		13[c]	I talked less than usual.
Sleep Disturbance		11[b]	My sleep was restless.
Depressed Mood		3[c]	I felt that I could not shake off the blues even with help from my family or friends.
		6[b]	I felt depressed.
		8[a,c]	I felt hopeful about the future.
		9[c]	I thought my life had been a failure.
		12[a,c]	I was happy.
		14[c]	I felt lonely.
		18[b]	I felt sad.
Pain	SF-12	5	During the past 4 weeks, how much did pain interfere with your normal work (including both work outside the home and housework)

Note. Center for Epidemiological Studies Depression Scale = CES-D; Medical Outcomes Study 12-item Short Form Health Survey = SF-12.

[a]These items were reverse scored before summation.

[b]These items were included based on those indicated by the developers of the revised CES-D (Eaton et al., 2004)

[c]These items were added by the research team based on expert consensus and the research literature.

Table 2

Symptom pattern identified by RRR among low income women under chronic stress participating in the HILDA and ALAS studies (n = 333)

Symptoms	Factor loading[a]	Standard score parameter[b]	Pearson's correlation[c]	Explained variation in score[d]
Pain	0.50	0.53	0.80	42.14
Depressed mood	0.52	0.47	0.83	39.42
Cognitive dysfunction	0.44	0.12	0.71	8.69
Fatigue	0.38	0.11	0.61	6.65
Sleep disturbance	0.38	0.05	0.60	3.11

Note.

[a] Factor loadings are directly obtained from RRR analysis; these are the loadings of each symptom on the latent symptom factor.

[b] Standard score parameters are obtained from multiple linear regression of symptoms on total symptom score; these are regression coefficients describing the strength of association of each symptom with the total symptom score.

[c] Pearson's correlation coefficient is the correlation of each individual symptom with the total symptom score.

[d] Explained variation is the total variation in the latent symptom factor (symptom score) explained by each symptom; it is calculated by multiplying standardized parameters with the Pearson's correlation coefficient x 100.

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