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Examining the Factorial Validity of Selected Modules from the Canadian Survey of Experiences with Primary Health Care

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Abstract

In this study, I examine the factorial validity of selected modules from the Canadian Survey of Experiences with Primary Health Care (CSE-PHC), in order to determine the potential for combining the items within each module into summary indices representing global primary health care concepts. The modules examined were Patient Assessment of Chronic Illness Care (PACIC), Patient Activation (PA), Managing Own Health Care (MOHC) and Confidence in the Health Care System (CHCS). Confirmatory factor analyses were conducted on each module to assess the degree to which multiple-observed items reflected the presence of common latent factors. While a four-factor model was initially specified for the PACIC instrument on the basis of prior theory and research, it did not fit the data well; rather, a revised two-factor model was found to be most appropriate. These two factors were labelled "Whole Person Care" and "Coordination of Care." The remaining modules studied here (i.e., PA, MOHC and CHCS) were all well represented by single-factor models. The results suggest that the original factor structure of PACIC developed within studies using clinical samples does not hold in general populations, although the precise reasons for this are not clear. Further empirical investigation will be required to shed more light on this discrepancy. The two factors identified here for PACIC, as well as the single factors produced for the PA, MOHC and CHCS could be used as the basis of summary indices for use in further analyses with the CSE-PHC.

Keywords: primary health care, confirmatory factor analysis, whole person care, coordination of care

Executive summary

The Canadian Survey of Experiences with Primary Health Care (CSE-PHC) was conducted by Statistics Canada in January and February 2007, on behalf of the Health Council of Canada. The purpose of CSE-PHC was to measure Canadians' experiences with the health care system: more specifically, their experiences with various types of physicians, access to health care, and use of different health care services including emergency rooms, clinics and prescription medications. CSE-PHC also assessed a number of attitudinal variables, such as Canadians’ confidence in the health care system and their perceptions of their role in managing their own health care.

Many of the CSE-PHC modules use multiple items to measure a smaller number of primary health care concepts. Therefore, researchers working with these data may wish to combine subsets of items into summary indices, in order to facilitate reporting of descriptive statistics as well as multivariate modelling. The purpose of this study is to examine whether the multiple items in each module have factorial validity, that is, whether they measure common dimensions or factors. Verification that a group of observed items measures a single latent factor is an important first step in constructing a summary or global index based on those items. Here, I focus on the factorial validity of the following four CSE-PHC modules: Patient Assessment of Chronic Illness Care (PACIC), Patient Activation (PA), Managing Own Health Care (MOHC) and Confidence in the Health Care System (CHCS).

I conducted a series of confirmatory factor analyses on the above modules to assess the degree to which multiple-observed items reflected the presence of common latent factors. A four-factor model was initially specified for the PACIC instrument on the basis of prior theory and research, but it did not fit the data well. Rather, a revised two-factor model was found to be most appropriate. These two factors were labelled: “Whole Person Care” and “Coordination of Care.” The remaining modules studied here—PA, MOHC and CHCS—were all well represented by single-factor models.

The results suggest that the original factor structure of PACIC, developed within studies using clinical samples, does not hold in general populations. However, the precise reasons for this are not clear, and further empirical investigation will be required to shed more light on this discrepancy. The two factors identified here for PACIC-as well as the single factors produced for PA, MOHC and CHCS-could be used as the basis of summary indices for use in further analyses with CSE-PHC.

1 Introduction

The Canadian Survey of Experiences with Primary Health Care (CSE-PHC) was conducted by Statistics Canada in January and February 2007 on behalf of the Health Council of Canada. The purpose of CSE-PHC was to measure Canadians' experiences with the health care system: more specifically, their experiences with various types of physicians, access to health care, and use of different health care services including emergency rooms, clinics and prescription medications. CSE-PHC also assessed a number of attitudinal variables, such as Canadians' confidence in the health care system and their perceptions of their role in managing their own health care. The sample selected for CSE-PHC consisted of 3,800 respondents (aged 18 and over) to Cycle 3.1 of the Canadian Community Health Survey (CCHS). The response rate for CSE-PHC was 58%, with a final sample size of 2,194. Further methodological details on CCHS and CSE-PHC are available elsewhere (Béland 2002, Statistics Canada 2007).

A number of the modules used on CSE-PHC use multiple items to measure a smaller number of primary health care concepts. Therefore, researchers working with CSE-PHC data may wish to combine item sets into summary indices representing these global primary health care concepts, in order to facilitate the reporting of descriptive statistics as well as multivariate modelling. The purpose of this study is to examine whether the multiple items in each module have factorial validity, that is, whether they measure a smaller number of common dimensions or factors. Verification that a group of observed items measures a single latent factor is an important first step in constructing a summary or global index based on those items. Here, I focus on the factorial validity of the following four CSE-PHC modules: (1) Patient Assessment of Chronic Illness Care, (2) Patient Activation, (3) Managing Own Health Care and (4) Confidence in the Health Care System.

The remainder of this report is organized as follows. Section 2—Survey Instrumentation—describes in more detail the specific CSE-PHC modules examined here. Section 3—Methodology—presents the theoretical and statistical underpinnings of factorial validity and describes the present strategy for factor-analysing the selected CSE-PHC modules. Section 4—Results—provides the results of the confirmatory factor analyses. Finally, Section 5—Discussion and conclusions—discusses how the results might inform the construction of summary indices as well as future use of these modules on national health surveys.

2 Survey instrumentation

2.1 The Patient Assessment of Chronic Illness Care module

On the Canadian Survey of Experiences with Primary Health Care (CSE-PHC), special attention was given to respondents who reported having one or more chronic health conditions. One module admistered exclusively to this subgroup was the Patient Assessment of Chronic Illness Care (PACIC) instrument. PACIC was designed by Glasgow and his associates (Glasgow et al. 2005) to measure key aspects of the Chronic Care Model (CCM) (Wagner et al. 1996, 1999), a conceptual framework developed for the evaluation and improvement of chronic illness care. Specifically, PACIC measures the following constructs (see Glasgow et al. 2005, Table 2, p. 439): (1) Patient Activation—actions that solicit patient input and involvement in decision-making; (2) Delivery System Design/Decision Support—actions that organize care and provide information to patients to enhance their understanding of care; (3) Goal Setting/Tailoring—acquiring information for and setting of specific, collaborative goals; (4) Problem-Solving/Contextual—considering potential barriers and the patient's social and cultural environment in making treatment plans; and, (5) Follow-up/Coordination—arranging care that extends and reinforces office-based treatment, and making proactive contact with patients to assess progress and coordinate care.

A modified version of PACIC was used in CSE-PHC (Appendix A, Table A1). Due to redundancy with other items on the survey, two items from the Patient Activation (PA) subscale were removed. Adjustments were also made to the preamble and the wording of some questions, in order to facilitate understanding of the concepts and the relevance of the questions. Typically, the reference period used on the original PACIC instrument is the previous six months; however, in order to accommodate respondents who may not have been actively treated during this time frame, CSE-PHC uses the stem "Over the past six months or when you last received care for your chronic condition(s)…." In addition, a skip pattern was introduced for the questions referring to a "treatment plan" to allow for the situation where a copy of a treatment plan was never formally provided to the patient.

Responses to all questions were provided on the following Likert-type scale: 1 = almost never, 2 = generally not, 3 = sometimes, 4 = most of the time, 5 = almost always.

2.2 The Patient Activation module

The 22-item PA (Hibbard et al. 2004) module is designed to measure patients' perceptions of their capacity to assume responsibility for their own health care. More specifically, PA presents a series of statements relating to the knowledge, confidence and skill necessary for patient self-management and collaboration with health care service providers. Patients indicate the extent of their agreement with each statement using the following scale: 1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree. A 10-item subset of the original PA was used on CSE-PHC (Appendix A, Table A2). As with PACIC, the 10-item PA was administered only to patients who reported having at least one chronic condition.

2.3 Managing Own Health Care module

The 3-item Managing Own Health Care (MOHC) module was created specifically for CSE-PHC and is similar to PA; it was designed to measure perceived responsibility and self-efficacy concerning the management of one's own health care (Appendix A, Table A3). Unlike PA and PACIC, however, it was administered to all CSE-PHC respondents. MOHC uses the following response scale: 1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree.

2.4 Confidence in the Health Care System module

To complement the measurement of peoples' attitudes toward their own role in their health care, the 3-item Confidence in the Health Care System (CHCS) module was used to assess individuals' views on the quality of the Canadian health care system, as well as the extent to which people believed modifications to the system were required. CHCS was administered to all CSE-PHC respondents. Response categories differed for each of the three CHCS items (Appendix A, Table A4).

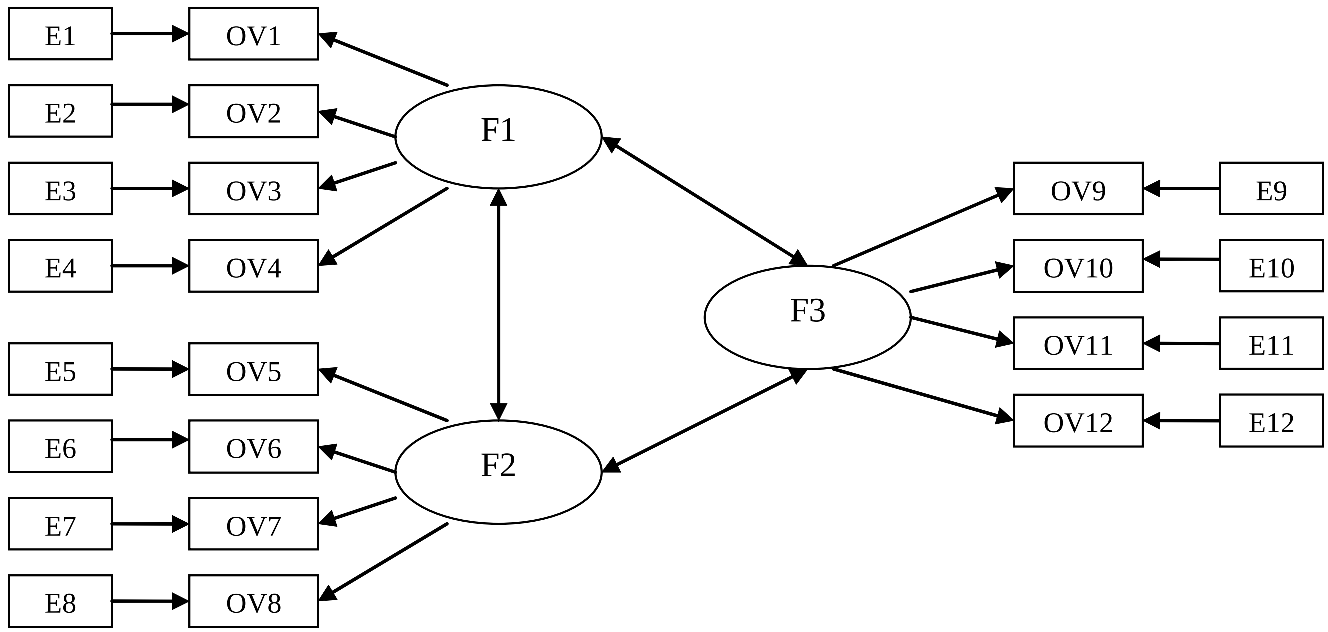
3 Methodology

3.1 Factorial validity and factor analysis: An overview

Factorial validity is an important aspect of a broader psychometric property known as construct validity, which can be defined as the extent to which an instrument measures what it is intended to measure. Often in social science research, the variables of interest cannot be measured directly, that is, they are latent rather than directly observable. However, information about latent variables can be obtained indirectly through multiple observed variables. More specifically, multiple-observed variables are designed to measure a single latent variable of theoretical interest. Not surprisingly, no single observed variable perfectly reflects the latent variable. However, one expects that multiple-observed indicators of a latent variable will covary, due to their mutual dependence on the latent variable. When the observed items on a measuring instrument show patterns of covariation consistent with the presence of one or more hypothesized underlying factors, the instrument is said to possess factorial validity. Factorial validity is an essential property for a measuring instrument, since it is the primary justification for aggregation of individual items into a meaningful overall score, or perhaps into different subscale scores, for use in subsequent descriptive or inferential analyses, for example, multivariate modelling).

Confirmatory factor analysis (CFA) is the statistical procedure of choice for assessing factorial validity, when an instrument has been designed in accordance with a conceptual framework specifying both the nature and number of underlying factors (Mulaik 1988). Put another way, the researcher possesses *a priori* knowledge of what the factors are, as well as which observed items are supposed to reflect them. The general form of a CFA model is best conveyed visually (Figure 1).

Figure 1
Diagram of generic confirmatory factor analysis model



As shown in Figure 1, the model asserts the existence of three factors, represented by ellipses—labelled here as F1 to F3—that are each reflected by four observed variables represented by rectangles—labelled here as OV1 to OV12. The arrows pointing to the observed variables from the factors imply that the factors are the explanatory variables and the observed variables are the outcomes. Statistically, these hypothesized links are modelled as regressions of the observed variables on the latent variables. Further, analogous to the more typical multiple regression case where both the explanatory and outcome variables are directly observed, error terms—represented by rectangles labelled here as E1 to E12—are included in the model to account for variance in the observed items not explained by the factors. Finally, the double-headed arrows connecting the factors themselves indicate that the factors can be correlated. Typically, orthogonal or completely independent factors are the exception rather than the rule in CFA applications.

It is important to note that the relations that are "absent" from Figure 1 are just as conceptually and statistically meaningful as those presented in the model. First, the model maintains that only one factor causes responses to a given item. For example, OV1 is allowed to relate only to F1, and its regressions on F2 and F3 are set equal to zero. Further, no correlations are allowed among the measurement error terms, that is, it is believed that there are no associations among the observed variables above those already explained by their mutual association with the factor(s). Of course, in any given CFA application the empirical data may refute these *a priori* restrictions. Therefore, CFA is a powerful statistical technique, allowing for potential disconfirmation of a given factor model, and even corresponding revisions of both the background theory and the measuring instrument.

Confirmatory factor analysis has some advantages over Cronbach's coefficient alpha (α) (Cortina 1993, Green and Hershberger 2000, Miller 1995), the traditional procedure for examining the integrity of psychometric scales. First, α tends to favour longer instruments, even those containing substantial amounts of measurement error, while penalizing shorter ones. In contrast, the quality of CFA results will not necessarily continue to increase as more observed variables are added to the model. Second, α is inflated by correlations among measurement errors, and can therefore give the impression that a set of items used to capture a single latent variable are better than they actually are. In CFA and EFA, variance due to measurement error is estimated separately from the variance of the factors. Correlations among the measurement error terms do not contribute to the factors themselves. Third, α was designed for use with continuous variables only, yet most instruments used in social science research are ordered categorical (ordinal). Thus applying α to ordinal variables can produce distorted results. Thanks to recent advances in statistical theory and computer programming, however, both CFA and EFA can properly handle ordinal variables (Flora and Curran 2004, Muthén and Muthén 2005).

3.2 General analytical strategy and estimation method

The Canadian Survey of Experiences with Primary Health Care (CSE-PHC) modules under consideration here were designed to measure clearly defined theoretical concepts, and therefore CFA is the technique applied here. If the CFAs reveal any poorly fitting models, modification indices will be used to determine the most appropriate way to revise the model.

All CFAs were carried out using the M*plus* software package (Version 4.1; Muthén and Muthén 2005). A Robust Weighted Least Squares estimation procedure was used (Flora and Curran 2004; Muthén, du Toit and Spisic in press), since the observed variables had ordinal response categories (i.e., 3-, 4- and 5-point rating scales). Under this procedure, it is assumed that for each observed survey item, the crude ordinal response categories correspond to 'thresholds' on a truly continuous, normally distributed response variable. This assumption is reasonable in the majority of applications. For example, there will usually be a true continuum of 'agreement' with survey items measuring attitudes, even though for operational reasons only a limited number of response categories (e.g., 1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree) are provided. The location of the respondent's attitude along this underlying continuum drives his or her placement among the limited response options. Put another way, a person is believed to fall into a given discrete category on the observed scale because they exceeded a given threshold value on the continuous response variable. This assumption is statistically convenient. For each observed ordinal variable, the sample proportions in the response categories can be used to estimate a set of threshold values (z-scores) on the corresponding continuous response variable. This approach also allows for the estimation of correlations among multiple continuous response variables rather than simply correlations among the observed ordinal items. These correlations are known as *polychoric* correlations and they can be used along with the threshold values as input for the factor analysis model. This strategy is superior to the more common approach of treating ordinal data as if they were continuous, and it does not produce distorted results in factor analysis models (Muthén and Kaplan 1992).

It is also important to point out a key general issue that arises when estimating models involving latent variables. Specifically, both the variances of the latent variables and the regressions of the observed variables on the latent variables are unknown and also interdependent. Therefore, the factor model cannot be estimated without additional user-specified constraints. The method selected here was to simply standardize the factors (i.e., assign them all means of 0 and variances of 1). Another popular method is to fix one of the regression links between the factor and its observed indicators at some *a priori* value (usually 1). However, since a major objective here was to evaluate the degree to which each observed variable reflected its parent factor, each of these regressions was allowed to be freely estimated.

3.3 Survey sampling weights

To obtain unbiased estimates of the factor model parameters, sampling weights were applied to account for unequal selection probabilities (Asparouhov 2005, Kaplan and Ferguson 1999). Bootstrap variance estimates were not computed, since M*plus* does not have a facility for replicate weights.

3.4 Handling missing data

All of the "don't know" or "refusal" responses to the selected CSE-PHC survey modules were coded to missing values. To minimize the exclusion of records with missing data and build a more robust set of input statistics, an additional multivariate modelling step was conducted prior to the factor analysis. Specifically, a multivariate regression was carried out in which the observed factor indicators were simultaneously modelled as outcomes of the following covariates: age, sex, and education. It was assumed that the data on the factor indicators were missing at random (MAR) with respect to the covariates. The MAR assumption holds that missingness on a given outcome depends on other variables in the model, but not on the values of the outcome itself (Allison 2003, Little and Rubin 2002). In the current application, it was the "assumed" continuous response variables and not actually the observed ordinal factor indicators that were regressed on the covariates; therefore probit rather than linear regression was used. In this model, information from the complete case regressions was used to inform the incomplete case regressions. More precisely, M*plus* does not impute missing values; instead, the conditional distribution of the missing values is inferred or 'borrowed' from the complete data regressions, thereby compensating for the data gaps. For example, if the relation between an explanatory variable X and an outcome variable Y is known for some cases, it is possible to make educated guesses about the distribution of missing Y values, as long as information about X is known. The technique minimizes the number of cases that are discarded due to incomplete data, which in turn increases power and reduces bias in parameter estimates. In the current analysis, each case was able to contribute statistical information to the regression analysis, provided that it met the following two minimum requirements: complete data on all selected covariates; and, at least one observed factor indicator. Household income was not used as a covariate, because it had large amounts of missing data (306 cases or 14% of the total sample).

In the second step, the statistics produced by the multivariate probit regressions of the factor indicators on the covariates were all used as input for the CFA model. (see Muthén and Muthén 2005, Muthén et al. in press). This approach is superior to simple listwise or pairwise deletion of cases with missing data. Both of these techniques require the data to be missing completely at random (MCAR), that is, missingness cannot depend on either the values of the variable in question or on other variables in the model. The MCAR assumption is dubious in the majority of applications (Allison 2003, Little and Rubin 2002). Another advantage of involving the covariates (i.e., age, sex, and education) in the CFA is that they can be used to directly predict the factors, thereby adjusting the model for such important variables as socio-demographic characteristics.

3.5 Assessing model fit

A variety of indices were used to assess the fit of the factor models. To test the overall goodness-of-fit, the chi-square (χ^2) statistic was used. The χ^2 tests whether the data differ from the form implied by the model, within sampling error. However, χ^2 is positively correlated with sample size if the model is not exactly correct (Browne and Cudeck 1993). Given that most statistical models are at best approximations of reality rather than exact matches, it is usually not reasonable to demand a nonsignificant χ^2 test statistic (McDonald and Marsh 1990). Therefore, χ^2 was supplemented with three widely used approximate fit indexes that are for the most part unaffected by sample size: the Comparative Fit Index (CFI) (Bentler 1990), the Tucker-Lewis Fit Index (TLI) (Bentler and Bonett 1980) and the Root Mean Squared Error of Approximation (RMSEA) (Steiger 2000).

CFI compares the fit of the theoretical model with the fit of an alternative ‘null’ model that assumes the observed variables are completely uncorrelated. CFI ranges from 0 to 1. The closer the CFI value is to 1, the more of an improvement the theoretical model is over the null model. A value of .90 or greater is generally taken as indicating a good-fitting model (Bentler 1990). TLI also assesses the fit of the theoretical model relative to a null model, but provides an adjustment for the degrees of freedom (df). In CFA applications, df are the number of areas in which the data are ‘free’ to deviate from the form implied by the model. Thus, model fit should be considered in light of how many places where discrepancies can arise; in other words, models with higher df should be afforded greater leniency, since they have a higher probability of being disconfirmed. As with CFI, the TLI values of 0.90 or greater indicate a well-fitting model. Unlike CFI, however, the TLI values can fall outside the 0 to 1 interval. Finally, RMSEA is a measure of absolute rather than relative fit. It measures the average amount of misfit between the model and the data, across all df. RMSEA has no theoretical upper limit, but has a lower bound that is 0. Lower values indicate better fit; values of 0.10 or less indicate an adequate fit (Browne and Cudeck 1993).

As well as global model fit, it is important to examine the individual parameter estimates. The magnitude of the regression coefficients linking factors to observed indicators reflects the degree to which the observed indicators measure the factors. In this study, these regressions are ordered probits, since the continuous response variables rather than the observed ordinal indicators are the outcomes of the factors. When standardized, the interpretation of these regressions coefficients—also called factor loadings—is as follows: on average, for each increase of one standard deviation unit in the factor, there is an *x* standard deviation unit change in the continuous response variable. Values of 0.30 or greater for factor loadings are usually taken to mean that the indicator is adequately reflecting the underlying factor (Comrey and Lee 1992). The statistical significance of the factor loadings was evaluated using critical ratio statistics (*z*-tests). The loadings were also adjusted for the effects of age, sex and education. Table 1 summarizes the different model fit assessment statistics.

Table 1
Model fit assessment statistics for confirmatory factor analysis

Fit statistic	Interpretation	Criterion values
χ^2	Overall discrepancy between theoretical model and observed data.	A p-value > 0.05 indicates a well-fittting model.
CFI	Fit of the theoretical model relative to a null model where all observed variables are uncorrelated; ranges from 0 to 1; higher scores mean better fit.	Values ≥ 0.90 indicate a well-fitting model.
TLI	Fit of the theoretical model relative to a null model where all observed variables are uncorrelated; adjusts for model df; can fall outside 0-1 interval; higher values mean better fit.	Values ≥ 0.90 indicate a well-fitting model.
RMSEA	Lack of fit of the theoretical model, per model df; values range from 0 to + lower values mean better fit.	Values ≤ 0.10 mean adequate fit.
Factor loading	Coefficient representing the regression of an observed variable on a factor; higher values indicate that the observed variable is a better representation of the factor.	A standardized coefficients ≥ 0.30 indicates adequate saturation of an observed variable by a factor.

4 Results

4.1 Confirmatory factor analysis of the Patient Assessment of Chronic Illness Care module

A 4-factor model was specified for the Patient Assessment of Chronic Illness Care (PACIC): (1) Problem-solving/Contextual, (2) Goal-setting/Tailoring, (3) Delivery System Design/Decision Support, and (4) Follow-up/Coordination. All items were reverse-coded prior to the analysis so that higher scores meant more positively oriented views (i.e., 1 = almost never, 2 = generally not, 3 = sometimes, 4 = most of the time, 5 = almost always). As mentioned earlier, only one of the three items measuring Patient Activation was included in the Canadian Survey of Experiences with Primary Health Care (CSE-PHC): “Over the past six months or when you last received care for your chronic condition(s), were you asked for your ideas when you and your primary care provider made a treatment plan?” Since the intercorrelations of this item with the remaining items in its subscale were unavailable, an underlying factor could not be specified. Instead, the Patient Activation item from PACIC was adopted by the factor model for the Patient Activation (PA) module.

PACIC was asked of patients with chronic conditions only, and those who did not have a treatment plan were not asked the full suite of items: items I16 and I17 were skipped. As a result, two 4-factor models were estimated. The first was based on only respondents who indicated having a treatment plan (N = 613). The second added those who indicated not having a treatment plan (N = 318), by assigning the lowest score possible (i.e., 1 = almost never) to the skipped questions. This modification was made to maximize the available statistical information for evaluating the 4-factor model. Similar global fit measures and individual parameter estimates for these two models would suggest that all patients could be modelled simultaneously, regardless of treatment-plan status.

In the model for those having a treatment plan, 15 cases were excluded because of missing data on one or more covariates and/or all of the PACIC items. The 4-factor model differed significantly from the data according to the strict χ^2 test (χ^2 [df = 51, N = 598] = 296.880, $p < 0.001$). With the exception of the CFI, the model fit reasonably well according to the approximate fit indexes (CFI = 0.842; TLI = 0.892; RMSEA = 0.090). Factor loadings and intercorrelations are shown in Table 2. All loadings were significant at the 0.01 level (z-values > 2.56) and > 0.30, indicating that all items functioned as adequate representations of the hypothesized underlying factors. However, an unexpected finding was that the correlations among the Problem-solving/Contextual, Goal-setting/Tailoring, and Delivery System Design/Decision Support factors were all > 1.0 (see Table 3). These inadmissible correlation estimates indicate potential model misspecification.

Prior to examining this misspecification in more depth, the model was re-estimated for all patients with chronic conditions. For those patients who indicated that they had never received a treatment plan, values were imputed for the relevant items, that is, 1 = almost never. I also attempted to retain those responding "don't know" or "refusal" to the question on receipt of

Table 2
Four-factor model for Patient Assessment of Chronic Illness Care, respondents with treatment plan

Factors and survey items	Factor loading	z-statistic	Standardized factor loading
Problem-solving/Contextual			
Were you asked how your chronic condition affects your life?	0.650	15.844	0.652
Were you helped to plan ahead so you could take care of your chronic condition in hard times?	0.764	25.427	0.766
Did your primary care provider consider your values and traditions when he/she recommended treatment to you?	0.609	15.918	0.611
Were you helped to make a treatment plan that you could do in your daily life?	0.664	18.540	0.666
Goal-setting/Tailoring			
Were you asked questions about your health habits?	0.602	17.230	0.603
Were you asked about your goals in caring for your chronic conditions?	0.680	21.470	0.681
Were you helped to set specific goals to improve your eating or exercise?	0.672	22.283	0.673
Were you encouraged to go to a specific group or class such as an educational seminar to help cope with your chronic condition?	0.646	16.518	0.646
Were you given a copy of your treatment plan?	0.474	10.161	0.474
Delivery System Design/Decision Support			
Were you shown that what you did to take care of yourself influenced your chronic conditions?	0.716	19.692	0.721
Were you given a written list of things you should do to improve your health?	0.624	14.952	0.629
Were you satisfied that your care was well-organized?	0.534	10.978	0.540
Follow-up/Coordination			
Were you encouraged to attend programs in the community such as support groups or exercise classes that could help you?	0.716	16.713	0.718
Were you referred to a dietician, health educator, or counsellor?	0.587	12.333	0.589
Were you told how your visits with other types of doctors (e.g., specialists or surgeon) helped your treatment?	0.787	21.874	0.789
Were you asked how your visits with other medical doctors were going?	0.733	21.124	0.734
Were you contacted after a visit with your primary care providers to see how things were going?	0.605	13.910	0.607

Notes: Sample size is 598. All survey questions begin with the root: "Over the past six months or when you last received care for your chronic condition(s)..." The z-statistic is the factor loading divided by its standard error.
Source: Canadian Survey of Experiences with Primary Health Care.

Table 3
Factor correlations for Patient Assessment of Chronic Illness Care, 4-factor model, respondents with treatment plan

Factors	Problem-solving/ Contextual	Goal-setting/ Tailoring	Delivery System Design/Decision Support	Follow-up/ Coordination
Problem-Solving/Contextual	1.000	...	...	...
Goal-Setting/Tailoring	1.029	1.000	...	...
Delivery System Design/ Decision Support	1.052	1.169	1.000	...
Follow-up/Coordination	0.653	0.826	0.710	1.000

... not applicable
Notes: Sample size is 598. All correlation coefficients are significant at the 0.01 level.
Source: Canadian Survey of Experiences with Primary Health Care.

a treatment plan, using the missing-data method described previously. In this model, 31 cases were excluded because of missing data on one or more covariates and/or all of the PACIC items. This 4-factor model also differed significantly from the data according to the $\chi 2$ test ($\chi 2$ [df = 62, N = 936] = 483.809, $p < 0.001$) and showed similar approximate fit indices (CFI = 0.852; TL1 = 0.919; RSMEA = 0.085). Factor loadings and intercorrelations are shown in Table 4. All coefficients were significant at the 0.01 level (z-values > 2.56) and > 0.30, indicating that all items functioned as adequate representations of the hypothesized underlying factors. As with the previous model, factor correlations 1.0 were found: Problem-solving/Contextual with Goal-setting/Tailoring, and Goal-setting/Tailoring with Delivery System Design/Decision Support (see Table 5).

Table 4
Four-factor model for Patient Assessment of Chronic Illness Care respondents with and without treatment plan

Factors and survey items	Factor loading	z-statistic	Standardized factor loading
Problem-solving/Contextual			
Were you asked how your chronic condition affects your life?	0.636	19.993	0.640
Were you helped to plan ahead so you could take care of your chronic condition in hard times?	0.780	32.061	0.783
Did your primary care provider consider your values and traditions when he/she recommended treatment to you?	0.590	17.727	0.594
Were you helped to make a treatment plan that you could do in your daily life?	0.715	26.116	0.718
Goal-setting/Tailoring			
Were you asked questions about your health habits?	0.624	21.782	0.626
Were you asked about your goals in caring for your chronic conditions?	0.735	32.071	0.736
Were you helped to set specific goals to improve your eating or exercise?	0.718	30.751	0.719
Were you encouraged to go to a specific group or class such as an educational seminar to help cope with your chronic condition?	0.704	23.566	0.705
Were you given a copy of your treatment plan?	0.625	17.977	0.626
Delivery System Design/Decision Support			
Were you shown that what you did to take care of yourself influenced your chronic conditions?	0.744	26.692	0.749
Were you given a written list of things you should do to improve your health?	0.686	21.716	0.692
Were you satisfied that your care was well-organized?	0.530	13.082	0.536
Follow-up/Coordination			
Were you encouraged to attend programs in the community such as support groups or exercise classes that could help you?	0.763	24.873	0.764
Were you referred to a dietician, health educator, or counsellor?	0.657	18.429	0.658
Were you told how your visits with other types of doctors (e.g., specialists or surgeon) helped your treatment?	0.762	26.377	0.763
Were you asked how your visits with other medical doctors were going?	0.722	25.291	0.723
Were you contacted after a visit with your primary care providers to see how things were going?	0.644	19.112	0.645

Notes: Sample size is 936. All correlation coefficients are significant at the 0.01 level. The z-statistic is the factor loading divided by its standard error.
Source: Canadian Survey of Experiences with Primary Health Care.

Table 5
Factor correlations for Patient Assessment of Chronic Illness Care, 4-factor model, respondents with and without treatment plan

Factors	Problem-solving/ Contextual	Goal-setting/ Tailoring	Delivery System Design/Decision Support	Follow-up/ Coordination
Problem-solving/Contextual	1.000	...	...	...
Goal-setting/Tailoring	1.401	1.000	...	...
Delivery System Design/ Decision Support	0.996	1.077	1.000	...
Follow-up/Coordination	0.996	0.869	0.796	1.000

... not applicable
Notes: Sample size is 936. All correlation coefficients are significant at the 0.01 level.
Source: Canadian Survey of Experiences with Primary Health Care.

The statistically improper factor correlation estimates suggest that the original factor model for PACIC (Glasgow et al. 2005) is not appropriate for the current data. In particular, these results indicate that these factors cannot be empirically distinguished in this sample. Thus a new factor model was specified where Problem-solving/Contextual, Goal-setting/Tailoring, Delivery System Design/Decision Support were collapsed into a single factor; and the Follow-up/Coordination items were loaded on a separate factor. The new, broader factor would seem to represent aspects of care that could be collectively referred to as Whole Person Care, while the other factor covers Coordination of Care.

This 2-factor model differed significantly from the data according to the $\chi 2$ test ($\chi 2$ [df = 65, N = 936] = 502.319, $p < 0.001$), and showed the following values for the approximate-fit indices: CFI = 0.846; TL1 = 0.920; RSMEA = 0.085. Inspection of the modification indices showed that a Goal-setting/Tailoring item placed on the new Whole Person Care factor also loaded strongly on the Coordination of Care factor: "Over the past six months or when you last received care for your chronic condition(s), were you encouraged to go to a specific group or class such as an educational seminar to help cope with your chronic condition?" The model was re-specified to have this item reflect both Whole Person Care and Coordination of Care, and model fit was as follows: ($\chi 2$ [df = 64, N = 936] = 371.652, $p < 0.001$; CFI = 0.892; TL1 = 0.943; RSMEA = 0.072. However, the above-noted item now no longer loaded on Whole Person Care, and so a final model was specified in which it loaded only on Coordination of Care. Model fit was as follows: ($\chi 2$ [df = 65, N = 936] = 378.164, $p < 0.001$; CFI = 0.890; TL1 = 0.942; RSMEA = 0.072). Factor loadings are shown in Table 6. All coefficients were significant at the .01 level (z-values > 2.56) and > 0.30, indicating that all items functioned as adequate representations of the hypothesized underlying factors. The factors of Whole Person Care and Coordination of Care were positively correlated at $r = 0.719$ ($p < 0.01$).

4.2 Confirmatory factor analysis of the Patient Activation module

A 1-factor model was specified for the Patient Activation (PA) module. In addition to the 10 PA items, the single patient activation item from PACIC was included in the model. All items were reverse-coded prior to the analysis so that higher scores meant more positively oriented views, that is, 1 = strongly disagree, 2 = disagree, 3 = agree, 4 = strongly agree). The total available sample size was 935 (32 cases were excluded due to missing data on one or more covariates and/or all of the PA items). The 1-factor model differed significantly from the data according to the $\chi 2$ test ($\chi 2$ [df = 44, N = 935] = 272.801, $p < 0.001$) but fit quite well according to the approximate-fit indexes (CFI = 0.940; TLI = 0.974; RMSEA = 0.075). All coefficients were significant at the 0.01 level (z-values > 2.56) and > 0.30, indicating that all original PA items functioned as adequate representations of the hypothesized underlying factor. However, the patient activation item from PACIC had a low standardized loading (0.238) compared with those of the original PA items (range: 0.671 to 0.843). Thus it seemed as though, in the context of the PA module, the PACIC patient activation item was a much poorer reflection of the underlying construct than the remaining items.

Table 6
Two-factor model for Patient Assessment of Chronic Illness Care, respondents with and without treatment plan

Factors and survey items	Factor loading	z-statistic	Standardized factor loading
Whole Person Care			
Were you asked how your chronic condition affects your life?	0.647	21.407	0.648
Were you helped to plan ahead so you could take care of your chronic condition in hard times?	0.794	36.398	0.795
Did your primary care provider consider your values and traditions when he/she recommended treatment to you?	0.602	17.744	0.603
Were you helped to make a treatment plan that you could do in your daily life?	0.729	26.862	0.730
Were you asked questions about your health habits?	0.659	23.014	0.660
Were you asked about your goals in caring for your chronic conditions?	0.773	34.767	0.774
Were you helped to set specific goals to improve your eating or exercise?	0.756	33.439	0.757
Were you given a copy of your treatment plan?	0.659	18.834	0.660
Were you shown that what you did to take care of yourself influenced your chronic conditions?	0.776	35.569	0.777
Were you given a written list of things you should do to improve your health?	0.717	25.295	0.718
Were you satisfied that your care was well-organized?	0.549	13.765	0.550
Coordination of Care			
Were you encouraged to attend programs in the community such as support groups or exercise classes that could help you?	0.763	27.555	0.763
Were you referred to a dietician, health educator, or counsellor?	0.666	19.098	0.667
Were you told how your visits with other types of doctors (e.g., specialists or surgeon) helped your treatment?	0.776	26.251	0.777
Were you asked how your visits with other medical doctors were going?	0.737	25.080	0.738
Were you contacted after a visit with your primary care providers to see how things were going?	0.656	19.477	0.657
Were you encouraged to go to a specific group or class such as an educational seminar to help cope with your chronic condition?	0.805	30.100	0.806

Note: Sample size is 936. All survey questions begin with the root: "Over the past six months or when you last received care for your chronic condition(s)…." The z-statistic is the factor loading divided by its standard error.
Source: Canadian Survey of Experiences with Primary Health Care

Therefore, a second CFA, which excluded the patient activation item from PACIC, was estimated for the PA module. This model showed similar fit to the previous PA model: $\chi2$ [df = 39, N = 934] = 277.984, $p < 0.001$; CFI = 0.936; TLI = 0.974; RMSEA = 0.081). Factor loadings were all significant at the 0.01 level (z-values > 2.56), and they are shown in Table 7.

4.3 Confirmatory factor analysis of the Managing Own Health Care and Confidence in the Health Care System modules

The factorial validity of the 3-item Managing Own Health Care (MOHC) and Confidence in the Health Care System (CHCS) modules was assessed within a single confirmatory factor analysis. Both modules were included because a factor model consisting of only three observed items cannot be statistically tested (Bollen 1989). A sample size of 2,143 was available for this analysis (51 cases were excluded because of missing data on one or more covariates and/or all of the scale items). The 2-factor model did not fit the data according to the $\chi2$ test ($\chi2$ [df = 20, N = 2143] = 73.792, $p < 0.001$); however, the approximate-fit indexes showed a very close fit (CFI = 0.985; TLI = 0.981; RMSEA = 0.041). Further, all factor loadings were significant at the 0.01 level (z-values > 2.56) and > 0.30 (See Table 8). Not surprisingly, the MOHC and CHCS factors were only weakly correlated ($r = .11$, $p < 0.01$), as the main motivation for inclusion of both factors was practical rather than theoretical.

Table 7
One-factor model for Patient Activation

Factors and survey items	Factor loading	z-statistic	Standardized factor loading
Patient Activation			
I am confident that I can take actions that will prevent or minimize some symptoms or problems associated with my health condition.	0.730	30.308	0.733
I am confident I can tell my primary care providers concerns I have even when he or she does not ask.	0.784	37.173	0.787
I am confident that I can follow through on medical treatments I need to do at home.	0.801	37.676	0.804
I am confident I can figure out solutions when new situations or problems arise with my health condition.	0.761	33.334	0.764
I am confident that I can maintain lifestyle changes in times of stress.	0.667	28.981	0.671
I know what each of my prescribed medications do.	0.771	28.639	0.774
I understand the nature and causes of my health condition.	0.821	39.690	0.824
I know the different medical treatment options available for my health condition.	0.800	41.482	0.803
I know how to prevent further problems with my health condition.	0.840	52.362	0.843
I have been able to maintain the lifestyle changes for my health that I have made.	0.799	39.437	0.802

Note: Sample size is 935. All survey questions begin with the root: "Over the past six months or when you last received care for your chronic condition(s)…." The z-statistic is the factor loading divided by its standard error.
Source: Canadian Survey of Experiences with Primary Health Care.

Table 8
Two-factor model for Managing Own Health Care and Confidence in the Health Care System

Factors and survey items	Factor loading	z-statistic	Standardized factor loading
Managing Own Health Care			
When all is said and done, I am the person responsible for managing my own health.	0.798	47.120	0.799
Taking an active role in my own health care is the most important factor in determining my health and ability to function	0.918	50.794	0.918
I am confident that I can tell when I need to go get health care and when I can handle a health problem myself.	0.718	38.727	0.720
Confidence in Health Care System			
Overall, how confident are you that if you became seriously ill, you will get quality and safe health care when you need it?	0.749	26.551	0.755
Overall, would you say that your confidence in the health care system is: rising, falling, or about the same as it ever was?	0.724	26.994	0.730
What approach would you say that Canada's health system requires at present: a complete rebuilding from the ground up, some fairly major repairs, some minor tuning up, or is everything fine the way it is?	0.695	26.954	0.702

Note: Sample size is 2,143. All survey questions begin with the root: "Over the past six months or when you last received care for your chronic condition(s)…." The z-statistic is the factor loading divided by its standard error.
Source: Canadian Survey of Experiences with Primary Health Care.

5 Discussion and conclusions

The results of the CFAs (confirmatory factor analysis) showed good cohesiveness of the Patient Activation (PA), Managing Own Health Care (MOHC), and Confidence in the Health Care System (CHCS) modules. For convenience of use in subsequent multivariate regression analyses, it would be reasonable to aggregate the items within these modules into single indexes, to be employed as either predictors or outcomes depending on the research questions. Alternatively, if one wanted to test a complex system of pathways among these and other constructs measured in the Canadian Survey of Experiences with Primary Health Care (CSE-PHC), each of these three modules could be treated as a latent variable in a structural equation model (SEM). In this case, all available observed indicators within each module would be used to reflect a single latent variable, just as in the confirmatory factor analyses conducted here.

On the other hand, the Patient Assessment of Chronic Illness Care (PACIC) module did not exhibit the same degree of integrity as the other modules, showing results discrepant with the original factor structure proposed by Glasgow et al. (2005). The new, 2-factor structure-Whole Person Care and Coordination of Care-tested in the CFA better suited the PACIC data, particularly by eliminating the problem of the inadmissible correlation estimates, that is, r's > 1.0. It is difficult to pinpoint exactly why the optimal-factor model differed markedly from those found in the original work on development of PACIC. Possible reasons might include (1) the fact that the U.S. (Washington State) sample at Group Health-the organization where the survey was developed-included only respondents having health insurance; (2) differences in health care services planning and delivery between Group Health and providers in Canada; and, (3) differences between the characteristics of the general Canadian population and Group Health members. CSE-PHC was a general population survey and it did not focus on patients who were being actively treated within a structured program such as that provided by Group Health, which is based on the same chronic illness care model that informed the construction of PACIC itself. Thus, many of the items may not have seemed relevant to CSE-PHC respondents, which could have resulted in the original PACIC factors not emerging distinctly in the present analysis.

Furthermore, it is possible that modifications made to PACIC for use on CSE-PHC may have influenced the factor-analysis results. These changes included removal of two items from the patient-activation subscale, changing the reference period from "the last six months" to "the last six months or when you last received care for your chronic conditions," and introducing a skip pattern for those indicating not having a treatment plan. Further psychometric research is certainly required to reveal the specific source of the discrepancies between the current findings and the original studies in which PACIC was developed.

However, the current evidence in the Canadian context suggests that if one wanted to use PACIC to develop summary indices, then the items within Whole Person Care and Coordination of Care could be reasonably aggregated. However, these two factors do require further consideration and conceptual refinement in order to ensure that they are fully understood and appropriately labelled.

Future waves of CSE-PHC may wish to use abbreviated versions of PACIC. If an overall index is desired, it may be possible to shorten PACIC by selecting a subset of items showing the highest loadings here on Whole Person Care and Coordination of Care. It is also important to note that in cases where the goal is not to produce summary indices for PACIC but rather collect specific bits of information about chronic illness care, then factor analysis results may be of limited utility for deciding on the most important items to include. In this case, selection of PACIC items will need to be based on other criteria: for example, relevance of each item to the specific target population.

Appendix

Table A1
Patient Assessment of Chronic Illness Care module

Problem-solving/Contextual
Were you asked how your chronic condition affects your life?
Were you helped to plan ahead so you could take care of your chronic condition in hard times?
Did your primary care provider consider your values and traditions when he/she recommended treatment to you?
Were you helped to make a treatment plan that you could do in your daily life?

Goal-setting/Tailoring
Were you asked questions about your health habits?
Were you asked about your goals in caring for your chronic conditions?
Were you helped to set specific goals to improve your eating or exercise?
Were you encouraged to go to a specific group or class such as an educational seminar to help cope with your chronic condition?
Were you given a copy of your treatment plan?[1]

Delivery System Design/Decision Support
Were you shown that what you did to take care of yourself influenced your chronic conditions?
Were you given a written list of things you should do to improve your health?
Were you satisfied that your care was well-organized?

Follow-up/Coordination
Were you encouraged to attend programs in the community such as support groups or exercise classes that could help you?
Were you referred to a dietician, health educator, or counsellor?
Were you told how your visits with other types of doctors (e.g., specialists or surgeon) helped your treatment?
Were you asked how your visits with other medical doctors were going?
Were you contacted after a visit with your primary care providers to see how things were going?

1 This item had an additional response category: 6 = never/no treatment plan.
Notes: All survey questions begin with the root: "Over the past s months or when you last received care for your chronic condition(s)..."
Response categories are 1 = almost always, 2 = most of the time, 3 = sometimes, 4 = generally not, 5 = almost never.
Source: Canadian Survey of Experiences with Primary Health Care.

Table A2
Patient Activation module

I am confident that I can take actions that will prevent or minimize some symptoms or problems associated with my health condition.
I am confident I can tell my primary care providers concerns I have even when he or she does not ask.
I am confident that I can follow through on medical treatments I need to do at home.
I am confident I can figure out solutions when new situations or problems arise with my health condition.
I am confident that I can maintain lifestyle changes in times of stress.
I know what each of my prescribed medications do.
I understand the nature and causes of my health condition.
I know the different medical treatment options available for my health condition.
I know how to prevent further problems with my health condition.
I have been able to maintain the lifestyle changes for my health that I have made.

Note: Response categories are: 1 = strongly agree, 2 = agree, 3 = disagree, 4 = strongly agree.
Source: Canadian Survey of Experiences with Primary Health Care.

Table A3
Managing Own Health Care module

When all is said and done, I am the person responsible for managing my own health.
Taking an active role in my own health care is the most important factor in determining my health and ability to function
I am confident that I can tell when I need to go get health care and when I can handle a health problem myself.

Note: Response categories are: 1 = strongly agree, 2 = agree, 3 = disagree, 4 = strongly agree.
Source: Canadian Survey of Experiences with Primary Health Care.

Table A4
Confidence in Health Care System module

Overall, how confident are you that if you became seriously ill, you will get quality and safe health care when you need it?[1]
Overall, would you say that your confidence in the health care system is…? [2]
What approach would you say that Canada's health system requires at present?[3]

1. Response categories are: 1 = very confident, 2 = somewhat confident, 3 = not very confident, 4 = not at all confident.
2. Response categories are: 1 = rising, 2 = falling, 3 = about the same as it ever was.
3. Response categories are: 1 = a complete rebuilding from the ground up, 2 = some fairly major repairs, 3 = some minor tuning up, 3 = everything is fine the way it is.
Source: Canadian Survey of Experiences with Primary Health Care.

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