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PACIC Instrument: disentangling dimensions using published validation models

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Abstract

Objective. To better understand the structure of the Patient Assessment of Chronic Illness Care (PACIC) instrument. More specifically to test all published validation models, using one single data set and appropriate statistical tools.

Design. Validation study using data from cross-sectional survey.

Participants. A population-based sample of non-institutionalized adults with diabetes residing in Switzerland (canton of Vaud).

Main outcome measure. French version of the 20-items PACIC instrument (5-point response scale). We conducted validation analyses using confirmatory factor analysis (CFA). The original five-dimension model and other published models were tested with three types of CFA: based on (i) a Pearson estimator of variance–covariance matrix, (ii) a polychoric correlation matrix and (iii) a likelihood estimation with a multinomial distribution for the manifest variables. All models were assessed using loadings and goodness-of-fit measures.

Results. The analytical sample included 406 patients. Mean age was 64.4 years and 59% were men. Median of item responses varied between 1 and 4 (range 1–5), and range of missing values was between 5.7 and 12.3%. Strong floor and ceiling effects were present. Even though loadings of the tested models were relatively high, the only model showing acceptable fit was the 11-item single-dimension model. PACIC was associated with the expected variables of the field.

Conclusions. Our results showed that the model considering 11 items in a single dimension exhibited the best fit for our data. A single score, in complement to the consideration of single-item results, might be used instead of the five dimensions usually described.

Keywords: chronic care model, validation analyses, confirmatory factorial analysis, diabetes

Introduction

The Chronic Care Model (CCM) was developed by Wagner *et al.* more than a decade ago [1, 2]. This evidence-based framework identified six key elements likely to improve the care of patients with chronic illnesses: patient's self-management, delivery system design, decision support, clinical information systems, community resources and policies, as well as organization of care. The Assessment of Chronic Illness Care (ACIC) [3] and Patient Assessment of Chronic Illness Care (PACIC) instruments were developed [4] to assess how chronic care was congruent with the CCM. While the ACIC was meant to be used by health care professionals, the PACIC was targeting the patients' evaluation of their own chronic illness care.

Initially developed in English [4], PACIC versions in Danish, Dutch, German and Spanish, tested in patients presenting diverse chronic diseases (e.g. diabetes, arthritis and chronic lung diseases), are available [4–15]. The literature review that we conducted to identify studies presenting validation analyses of the PACIC (Appendix 1) showed contrasted results. While some studies seemed to confirm the five dimensions of the instrument (moderate to good internal consistency and most factor loadings >0.70), they either did not report goodness of fit of their models [5, 6] or presented fits that were not acceptable [4, 9]. In the first published English PACIC validation paper, Glasgow recommended the use of a unique PACIC global score given because 'the intercorrelations among the PACIC scales and the high internal consistency of the total score' may make it difficult for respondents to recognize 'differences among the subscale constructs' [4]. Recently, findings suggested a single- [8, 14] or a two-dimension structure [10, 11]. Item reduction was even proposed to get a single

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dimension [7, 12, 14]. Despite the absence of consensus on the PACIC dimensions, its use has sharply increased as an evaluation tool of the development and implementation of chronic disease management initiatives. It has even been described as 'the most appropriate instrument to measure the experience of people receiving integrated chronic care' [16].

In this study, we aimed at deepening the understanding of the PACIC dimensional structure using statistical tools adapted to the ordinal structure. More specifically, we aimed at comprehensively describing previous validation analyses and at running all models tested in the literature on the same set of patients, using appropriate statistical models. This study should convey key information to decide which dimension structure is the most appropriate for this broadly used instrument.

Methods

Sample characteristics

The study sample comprised 406 patients with diabetes who participated in a community-based survey describing the quality of their care [17]. This *baseline* survey was conducted within the development and implementation of a regional diabetes program ('Programme cantonal Diabète') in the canton of Vaud, Switzerland, a large French-speaking canton with over 720 000 inhabitants (approximately one-tenth of the Swiss population). Non-institutionalized adults (≥18 years) with a diagnosis of diabetes since at least 1 year, receiving a prescription for oral antidiabetic medications (OAD), insulin, glycemic strips or glucose meter, were eligible and recruited by community-based pharmacies during the summer of 2011 [17]. Patients residing outside the canton of Vaud, not speaking or understanding French well enough, or those presenting cognitive impairment were excluded, as well as women with gestational diabetes.

Measures

A 20-item French version of the PACIC questionnaire (5-point response scale, 1 = never to 5 = always) was used. We translated and culturally adapted the English PACIC version in a structured approach, using forward and backward translations and following WHO [18] guidelines for such processes. First, two collaborators fluent both in French and English prepared a French version of the questionnaire that was discussed by a group of experts. After reaching consensus on a first French version, back translation was performed by a professional English-native translator. The expert group then compared the original and back-translated English versions, resolved discrepancies and agreed on a version that was tested among 10 various patients with diabetes.

Other self-reported data included patients' socio-demographics and health information: age, gender, socio-economic and insurance status, citizenship, place of residence, smoking status, weight and height, number of comorbidities, generic and disease-specific health-related quality of life, diabetes treatment, and 10 process of care indicators (past 12 months HbA1C check among those who reported knowing what HbA1C was, eye examination by ophthalmologist, micro-albuminuria check, foot examination by physician, lipid test, blood pressure measure, weight measure, influenza immunization, physical activity recommendations, written or verbal diet recommendations). We also collected data on proposal to participate in, and effective participation in self-management education classes, as well as glucose self-monitoring. Finally, we also asked patients to rate their overall care satisfaction level.

Statistical analysis

First, we conducted descriptive analyses to characterize participants and check data quality of each of the 20 PACIC items (mean, standard deviation, median, distribution by category (floor and ceiling effects), percentage of missing values). Then, we tested all the models described in published PACIC validation studies (Appendix 1): model with original five dimensions [4, 5, 6, 9, 15], two models suggesting two dimensions [10, 11], one model with a single dimension considering all 20 items [8, 14] and one model with a single dimension considering 11 out of the 20 PACIC items (PACIC-short form) [7, 12, 14]. Models not reporting enough details for replication [13] or not using the full 20-item scale [19] were discarded. Models testing was performed using three different types of confirmatory factor analysis (CFA): (i) CFA based on Pearson estimator of variance–covariance matrix, which hypothesizes multivariate normal distribution of the data, (ii) CFA based on a polychoric correlation matrix (weighted least squares estimation method (WLSMV) [20] and (iii) CFA based on a likelihood estimation with a multinomial distribution for the manifest variables (also called GLLVM [21, 22]). These three types of CFA assume that the latent variable (patients' evaluation of their chronic illness care) is a continuous and normally distributed concept. These three types of CFA were chosen for the following reasons: (i) CFA based on Pearson estimator because it had often been used in other studies and would allow us to compare our results with those previously published, even if these models should not be used with ordinal data; (ii) CFA considering polychoric correlation matrix because it relies on the assumption that the manifest variables measured on ordinal scales are indirect observations of underlying normal variables [23] and (iii) CFA based on likelihood estimations with a multinomial distribution for the manifest variables because they do not postulate any joint distribution for the manifest variable, since it computes the real joint distribution of the data [22]. In addition, these models are recommended in cases of asymmetric or multimodal distributions (i.e. in presence of ceiling and floor effects), and when the CFA polychoric correlation matrix may lead to biased results [24]. One limitation of the use of CFA based on likelihood estimations with multinomial distribution for the manifest variables is the absence in current software of goodness-of-fit measures that can assist in the comparison of models to one another.

Goodness of fit (GoF) of the various CFA models was tested using the Root Mean Square Error of Approximation (RMSEA) and Weighted Root Mean Square Residual (WRMR,

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recommended for ordinal data [25]). They were checked jointly because of the sensitivity to misspecified factor loading for the RMSEA [26]. The Comparative Fit Index (CFI) was also presented, since it is less affected by sample size [26–28]. Models were considered to present 'good fit' if the RMSEA was <0.05, [29], WRMR <1.00 [30] and CFI >0.97 [31]. Models were considered to have acceptable fit if RMSEA was between 0.05 and 0.08 and CFI between 0.95 and 0.97. Full Information Maximum Likelihood (FIML) estimation, which uses raw data as input and all available data information, was used to handle missing data for CFA based on Pearson estimator of variance–covariance matrix and for GLLVM. For CFA based on a polychoric correlation matrix, models were computed on the available data; multiple imputation of missing data using Baysian analysis was also performed.

Finally, we explored associations between the one dimension PACIC score (11 items) and other variables hypothesized, or already shown, to be related to it. Pearson or Spearman correlations were used to test the association between PACIC and continuous variables, *t*-test for independent groups, or Mann–Whitney *U*-test (when extreme values) for categorical variables. Stata 12 was used for most statistical analysis; Mplus 5.0 [20] was used to run CFA.

Results

Sample

The study population is described in Table 1. Mean age was 64.4 years and 59% were men. Smokers represented 16% of respondents, and 82% were either overweight or obese. Type 2 and Type 1 diabetes was reported in 69 and 18% of patients, respectively, while diabetes type remained undetermined for almost 20% of patients. At least one complication of diabetes was reported by nearly half of all patients.

Table I Characteristics of participants ($n = 406$ diabetic patients)

Age ($n = 406$)	mean (SD): 64.4 (11.4)
Women ($n = 406$)	40.6%
Civil status ($n = 403$)	
Single	8.7%
Married/partnership	62.5%
Divorced/separated/widowed	28.8%
Education ($n = 392$)	
Primary	19.1%
Secondary	55.6%
Tertiary	25.3%
Employment status ($n = 394$)	
Full-time	25.1%
Part-time	9.1%
Retired	55.6%
Unemployment/handicapped/student	5.8%
Stay-at-home	4.3%
Place of residence ($n = 399$)	
Urban	38.9%
Semiurban	27.1%
Rural	34.1%
Current smoking ($n = 398$)	16.3%
BMI ($n = 378$)	
Overweight and obese	82.0%
Self-reported health ($n = 398$)	
Excellent/very good	15.9%
Good	64.3%
Medium/poor	19.9%
Type of diabetes ($n = 406$)	
Type 1	12.8%
Type 2	68.5%
Undetermined	18.7%

PACIC scores

Table 2 provides descriptive results of PACIC items. While 77% of respondents completed all items of the questionnaire, the number of missing values varied between 6 and 12%. The percentage of respondents who ticked the lowest answering category (floor effect) varied from 7 to 67%, and was higher than 30% for 12 out of the 20 items. Ceiling effects were less marked (4–46% of respondents chose the highest answering category, and 5 out of 20 items presented ceiling effects >30%).

PACIC structure

The results of CFA considering polychoric correlations on the available data are presented in Table 3 (results on imputed data are nearly identical and not shown). The results demonstrate that although loadings of all five models were relatively high, the only model showing acceptable to good fit was the 11-item single dimension model (RMSEA <0.08, WRMR <0.1.00, CFI >0.97). Similar results were obtained with CFA based on likelihood estimations with multinomial distribution for the manifest variables, although slightly higher loadings were found for those items presenting the strongest floor or ceiling effects (items 10 and 17; differences <0.10). The 11-item single dimension model was also shown to be the best of the five tested models when CFA on Pearson estimator of variance matrix was used. This was only true in term of goodness of fit (RMSEA is <0.08 and CFI >0.95) because loadings were all shown to be lower than those of the CFA on polychoric correlation. As expected, conducting CFA analyses with a model for multivariate data, while data are ordinal, underestimated correlations (results not shown). The correlation matrix is available on Table 4 (polychoric correlations in the lower triangle and Pearson correlations in the upper triangle).

Relationship of factorial score of PACIC short form and variables of the field

The single 11-item dimension score was retained for these analyses. Respondents were significantly more likely to report

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Table 2 Data quality of the 20 PACIC items

Item	Mean	(SD)	Median	Response categories					Missing values
				Never[a] (1)	Generally not (2)	Sometimes (3)	Most of the time (4)	Always[b] (5)	
				Percent					
1	3.1	(1.6)	3	27.8	10.2	15.2	15.7	31.2	5.9
2	2.4	(1.5)	2	44.8	10.9	19.2	12.3	12.8	7.6
3	3.3	(1.5)	3	20.4	11.6	19.3	17.5	31.2	6.9
4	2.2	(1.4)	2	48.4	10.6	20.4	10.9	9.8	6.9
5	4.1	(1.2)	4	7.3	3.4	8.7	35.1	45.5	12.3
6	3.7	(1.3)	4	12.1	6.8	15.8	28.1	37.3	6.2
7	2.8	(1.5)	3	28.3	13.9	21.9	18.9	17.1	7.6
8	2.9	(1.4)	3	22.6	13.0	26.8	22.6	15.1	7.1
9	2.2	(1.5)	1	54.7	8.6	12.1	12.6	12.1	8.1
10	1.8	(1.2)	1	64.7	10.9	13.0	4.8	6.6	7.1
11	2.8	(1.4)	3	28.4	11.1	25.8	19.5	15.3	6.4
12	3.8	(1.3)	4	13.2	3.4	15.6	29.8	38.0	6.7
13	2.8	(1.6)	3	36.8	8.9	14.1	18.5	21.7	5.7
14	2.7	(1.5)	3	35.3	11.3	17.5	18.6	17.3	5.9
15	2.6	(1.4)	3	34.7	15.1	18.5	19.8	11.9	6.9
16	2.1	(1.3)	1	52.9	13.8	15.3	11.1	6.9	6.9
17	1.7	(1.1)	1	67.1	11.8	12.3	5.4	3.5	7.9
18	2.2	(1.4)	2	49.2	11.4	22.2	7.7	9.5	6.9
19	3.0	(1.6)	3	30.3	7.4	19.8	17.9	24.5	6.7
20	2.4	(1.6)	2	47.0	9.6	14.1	13.3	16.2	7.1

SD, standard deviation.
[a]Floor effect.
[b]Ceiling effect.

higher PACIC scores when treated with insulin, performing glucose self-monitoring, being aware of HbA1C, having had feet, eyes or microalbuminuria annual checks, having been proposed to attend, or participated, to education classes, having received physical activity or diet recommendations. PACIC factorial 11-item score was also significantly associated with age and overall care satisfaction (results not shown). There were no significant differences for gender, education, number of comorbidities, annual blood pressure, weight and lipid measures.

Discussion

The results of this study showed that among the several PACIC models proposed in the literature, only the one dimensional structure using 11 of the 20 PACIC items (PACIC short-form) presented appropriate model fit in addition to high loadings. Other published models, including the originally described five dimensions structure, were discarded because of poor statistical fits.

There are several explanations to the lack of consensus of results regarding the structure of the PACIC instrument across validation studies. Firstly, it may be possible that the initial five dimensions structure proposed by Glasgow was not the appropriate one, and that the PACIC contained less dimensions. In fact, Glasgow emphasized that the dimensions were constructed *a priori*, on the basis of the CCM key elements. He also pointed out that the inter-correlations among the PACIC dimensions could make it difficult to distinguish between them; this issue is supported statistically. Indeed, because the PACIC items are measured on an ordinal scale, using inappropriate models can lead to underestimating correlations and to the selection of too many dimensions [7]. In addition, several published models supported the idea of an instrument presenting fewer than five dimensions [7, 8, 10, 11, 13, 15]. Secondly, the inappropriate choice of statistical tools and parameters considered to assess the quality of the models may have affected results. Actually, several studies used CFA for multivariate normal data despite the presence of ordinal data; this may not only underestimate correlation but also impact the magnitude of the dimensions' loadings [7]. As a matter of fact, results of the three types of CFA were close, but loadings of the multivariate normal model were the lowest. This emphasizes the point that both the choice of statistical tools and the criteria of model selection may influence estimations of the elements of the models. In addition, considering the magnitude of loadings only, as selection criteria, is wrong since it is not a measure of goodness of fit (i.e. a measure of how well the model fits the observed data).

Interestingly, all studies supporting the five dimensions structure of the PACIC described either only loadings and no

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Table 3 Loadings and model fits of the five tested models (CFA based on polychoric correlation matrix)

	Model 1[a] ($n = 392$)					Model 2[b] ($n = 392$)		Model 3[c] ($n = 392$)		Model 4[d] ($n = 392$)	Model 5[e] ($n = 390$)
Item	Dim 1	Dim 2	Dim 3	Dim 4	Dim 5	Dim 1	Dim2	Dim 1	Dim2	Dim 1	Dim 1
1	0.82					0.73		0.73		0.72	
2	0.89					0.79		0.79		0.77	0.70
3	0.78					0.69		0.69		0.67	
4		0.70					0.71		0.67	0.65	
5		0.64				0.60		0.60		0.59	0.55
6		0.87				0.80		0.81		0.78	
7			0.83			0.83			0.84	0.82	
8			0.83			0.83			0.84	0.82	0.79
9			0.72				0.77		0.72	0.71	0.72
10			0.73				0.77		0.73	0.72	0.60
11			0.73			0.74			0.74	0.72	0.72
12				0.64		0.62		0.62		0.60	
13				0.84		0.80		0.81		0.79	0.82
14				0.79		0.76		0.77		0.75	0.79
15				0.85		0.81		0.82		0.80	0.83
16					0.61		0.61		0.58	0.56	0.59
17					0.87		0.84		0.81	0.80	
18					0.64		0.63		0.60	0.59	
19					0.75		0.74		0.70	0.69	0.66
20					0.75		0.75		0.70	0.69	
CFI			0.879			0.871		0.842		0.828	0.977
RMSEA			0.115			0.117		0.129		0.136	0.061
WRMR			1.364			1.446		1.577		1.652	0.736

CFI, Comparative Fit Index; RMSEA, Root Mean Square Error of Approximation; WRMR, Weighted Root Mean Square Residual.
[a]Glasgow [4]: The original five-dimension structure.
[b]Taggart [10]: a two dimensions structure.
[c]Gensichen [11]: a two dimensions structure.
[d]Gugiu [8]: a single dimension structure.
[e]Gugiu [7]: a single dimension structure considering 11 out of the 20 items.

GoF [5, 6], or GoF that was non-satisfactory [4]. Furthermore, most studies reporting loadings jointly with GoF, as should be done, rejected the five dimensions structure of the PACIC [8, 9, 13, 15] or sustained a one dimension model [7, 8, 14]. Thirdly, some studies reporting CFA results used samples smaller than the minimal 10 responses by item rule of thumb. Indeed, researchers should consider data sets including at least 200 patients while analyzing the structure of a 20-item instrument; required sample sizes should even be larger when using ordinal data, and samples of about 300 was suggested by some authors [32]. While two of the three studies favoring the PACIC five-dimension structure did not reach the minimal number of 200 patients, none of these three studies reached the target of 300 patients ($n = 100$ [5]; $n = 266$ [4]; $n = 165$ [6]). All other studies showing less than five dimensions used sample sizes greater than 300.

Based on this rationale, the PACIC instrument does not appear to present a five-dimensional structure. Studies indicating structures composed of one or two dimensions were also considered in our analyses. The tests of both models proposing two dimensions structures [10, 11] showed that factor loadings were good, but model fit was generally unacceptable. We also tested the 20-item single-dimension model showing acceptable model fits in two studies [8, 14]. Unfortunately, we did not find similar results. In the end, the single-dimension model considering 11 out of the 20 PACIC items was the model that fitted our data best and tests of this model in three other studies and demonstrated acceptable fit [7, 12, 14]. Therefore, all these results converged toward a single-dimension structure comprised of all 20, or a subset of 11 items.

The heterogeneity of structure results could also be linked to methodological considerations other than statistical ones. In fact, the PACIC versions used were not always identical, in terms of anchoring response categories ('almost always and almost never' versus 'always and never') and of number of response modalities (5-points versus 11-points). This could

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Table 4 Correlation matrix of the 20 items of the PACIC: polychoric correlations in the lower triangle and Pearson correlations in the upper triangle

	0.649	0.468	0.356	0.348	0.438	0.459	0.425	0.409	0.303	0.405	0.314	0.465	0.451	0.367	0.292	0.332	0.243	0.364	0.362
0.766		0.558	0.370	0.290	0.471	0.535	0.442	0.390	0.306	0.466	0.324	0.471	0.477	0.509	0.320	0.375	0.275	0.365	0.362
0.556	0.675		0.349	0.428	0.431	0.501	0.451	0.320	0.234	0.475	0.341	0.351	0.331	0.469	0.260	0.266	0.240	0.321	0.422
0.451	0.454	0.430		0.283	0.428	0.437	0.518	0.505	0.349	0.343	0.317	0.386	0.379	0.329	0.316	0.369	0.363	0.353	0.291
0.428	0.359	0.492	0.339		0.561	0.349	0.417	0.218	0.187	0.411	0.387	0.351	0.361	0.346	0.254	0.172	0.205	0.284	0.246
0.523	0.604	0.512	0.557	0.643		0.590	0.605	0.342	0.309	0.506	0.379	0.467	0.464	0.468	0.294	0.323	0.333	0.395	0.354
0.539	0.629	0.594	0.518	0.431	0.698		0.689	0.480	0.364	0.491	0.374	0.532	0.490	0.586	0.353	0.366	0.330	0.381	0.432
0.506	0.529	0.521	0.613	0.504	0.694	0.760		0.497	0.374	0.513	0.389	0.533	0.516	0.551	0.346	0.410	0.400	0.432	0.414
0.524	0.484	0.406	0.610	0.279	0.463	0.579	0.620		0.385	0.296	0.303	0.527	0.411	0.441	0.431	0.413	0.270	0.387	0.342
0.400	0.416	0.310	0.462	0.218	0.449	0.474	0.498	0.507		0.347	0.266	0.390	0.328	0.343	0.234	0.696	0.434	0.326	0.217
0.478	0.549	0.548	0.423	0.492	0.609	0.580	0.596	0.374	0.447		0.463	0.500	0.414	0.535	0.323	0.382	0.394	0.356	0.405
0.398	0.410	0.414	0.393	0.476	0.451	0.461	0.474	0.403	0.357	0.546		0.491	0.371	0.407	0.183	0.215	0.178	0.328	0.263
0.542	0.565	0.423	0.468	0.455	0.584	0.626	0.621	0.642	0.504	0.603	0.617		0.569	0.550	0.350	0.367	0.349	0.449	0.412
0.531	0.568	0.398	0.464	0.424	0.554	0.567	0.594	0.500	0.440	0.490	0.466	0.665		0.619	0.391	0.410	0.382	0.416	0.408
0.443	0.595	0.555	0.404	0.410	0.573	0.668	0.632	0.542	0.440	0.617	0.478	0.652	0.703		0.399	0.459	0.368	0.466	0.499
0.376	0.397	0.330	0.386	0.315	0.392	0.442	0.427	0.532	0.334	0.403	0.210	0.444	0.476	0.490		0.342	0.297	0.304	0.314
0.453	0.491	0.355	0.477	0.174	0.461	0.486	0.545	0.541	0.820	0.503	0.253	0.477	0.535	0.581	0.468		0.497	0.394	0.344
0.296	0.339	0.293	0.455	0.190	0.420	0.396	0.473	0.345	0.571	0.467	0.186	0.422	0.455	0.428	0.381	0.638		0.375	0.333
0.431	0.458	0.390	0.446	0.338	0.495	0.458	0.506	0.503	0.433	0.428	0.387	0.537	0.509	0.559	0.382	0.537	0.467		0.589
0.456	0.451	0.501	0.375	0.304	0.471	0.527	0.509	0.455	0.312	0.484	0.318	0.527	0.516	0.601	0.399	0.465	0.419	0.709	

potentially affect the number of described dimensions. However, published results did not appear to depend on these differences since, for example, the one dimension structure was validated both with 5- [14] and 11-point scales [7, 8]. Also, studies suggesting a five dimensional structure considered both the 'almost never' to 'almost always' [4, 6] and 'never' to 'always' [5] anchoring response categories.

The diversity of health care contexts, cultures and types of chronic illnesses may also have affected validation results. Evidence from studies favoring the single dimension structure (20 items: long or 11 items: short form) suggests that it is not the case. In fact, this single dimension was found in a variety of countries such as the USA [7, 8], Germany [12], the Netherlands [14] and Switzerland, and with patients presenting different chronic diseases (diabetes [7, 8], cardiovascular diseases [14], non-specific chronic illnesses [12]).

The strength of this study are the fact that (i) we used a single data set to test all published validation models, (ii) we used statistical tools appropriate for ordinal data and (iii) we presented model fits. The interpretation of these results should nevertheless take into consideration the following limitations. First, we did not aim to find the true underlying structure of the PACIC, but rather to disentangle dimensions focusing on published models. Therefore, we emphasized the analysis of the structure of the PACIC and not its construct validity, hypothesizing that the latter was appropriate. As suggested by Gugiu *et al.* [8] and Spider *et al.* [33], we strongly encourage researchers to focus future studies on the construct validity of the PACIC instrument. Second, we employed a newly developed French version of the PACIC. However, we strictly followed the translation and adaptation of questionnaires procedures, and our results were similar to others; this suggests that results do not depend on health care contexts, cultures or chronic diseases considered. Third, we did not perform test-retest measures that would have allowed the assessment of the reliability of the PACIC French version. Finally, this instrument, which relates to the past 6 months and uses a 5-point response scale varying from never to always, may not be easy to use for patients visiting their family doctor rather rarely (a few times a year, for example) and not seeing any other health care professional during that same period. Indeed, it may be difficult to decide whether an event happening once during 6 months represents a frequency that should be considered as 'sometimes', 'most of the time' or 'always' [8, 33]. This may be particularly true in contexts that have not yet implemented new models of care for patients with chronic diseases, and therefore do not offer integrated multidisciplinary care. One way to bypass this could be to replace the original 5-point scale by a count of time each situation occurred, which may be easier to use.

Conclusion

We showed that among PACIC published validation models, the one considering 11 items in a single dimension appeared to best fit our data. Also, our results suggested that the lack of consensus on the PACIC structure was linked to statistical problems rather than differences in health care contexts or cultures. To obtain an overall picture of experiences of people receiving care for chronic diseases, a single score might be used instead of the five previously described dimensions.

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Appendix

Appendix I Summary of PACIC validation analyses, as reported in published papers

Author Country Disease(s) targeted (sample size)	PACIC version	Type of analysis	Number of dimensions	Alpha cronbach	Test-retest	Data quality ceiling effect (CE) Floor effect (FE) Missing (M)	Goodness-of-fit (GoF), loadings (L), Other (O)	Associations with other variables
Glasgow USA Several chronic diseases (n = 266) [4]	Original validation[a]	CFA	5	0.77–0.93	r = 0.47–0.68 (n = 52–57)	CE: none FE: yes, but magnitude not specified M: 4%	GoF: Moderate fit (non-normed fit index = 0.87 and comparative fit index to assess model fit = 0.89) L: 0.54–0.89 with 3 items <0.70 O: 62–74% of explained variance	With[d]: age, gender, number of chronic conditions None[e]: education, overall health, years since diagnosis
Aragones USA Diabetes (n = 100) [5]	Spanish[b]	CFA	5	>0.60	r = 0.77 (n = 20)	CE: none FE: none M: NA	GoF: NA L: 13 items >0.70, 1 item <0.60 (most items correlated highly on proposed scales)	None[e]: comorbidities, age, education, country of origin, years living in the USA
Wensing Netherlands Diabetes or COPD (n = 165) [6]	Dutch (long/short form)[a]	PCA	5	0.71–0.93	NA	CE: 10–54% with >30% for 6 items FE: 7–76% with >30% for 11 items M: 22–35%	GoF: NA L: PA,DS & PS: 0.39–078; GS & FC: not ok O: 70% explained variance, KMO = 0.844, Bartlett's test of sphericity: P < 0.001	With[d]: EUROPEP score
Gugiu USA Type 2 diabetes (S1 n = 529, S2 n = 361) [7]	English short form (11 items)[c]	EFA within CFA (long form, S1); CFA on polychoric correlation matrix (short form, S2)	1	0.96 (ordinal omega)	r = 0.64 (n = 250)	Response modalities recoded into 3 categories due to moderate floor and ceiling effects	GoF: good for short form L: NA	None[e]: age, gender, education, income, marital status, insurance type, blood pressure, HbA1c, LDL cholesterol, microalbumin

Gugiu USA Type 2 diabetes (n = 529) [8]	PACIC (long/short form)[c]	CFA (polychoric correlation matrix) EFA on polychoric correlation matrix NB: response modalities recoded into 3 categories	1	0.97 (ordinal omega)	NA	CE: 43% FE: 24% M: 0.2–2.8% (8.9% at least one missing: multiple imputation performed)	GoF: poor for 5 dimensions L: NA O: 1–3 dimensions retained, 1 dimension more reliable	None[e]: clinical indicators
Maindal Denmark Diabetes (n = 481) [9]	Danish PACIC[b]	CFA for categorical measures	5	0.71–0.94	NA	CE: 4.0–40.4% with >15% for 12 items FE: 2.7–69.2%, with >15% for 17 items M: 0.5–2.9%	GoF: bad fits (chi2, CFI, RMSEA, WRMR not good) L: 0.31–0.77 (<0.60 for 8 items)	None[e]: age, gender
Taggart Australia Diabetes, IHD, HBP (S1 n = 2552, S2 n = 758) [10]	Original PACIC[b]	EFA	2	0.88–0.94	NA	CE: NA FE: NA M: 27% (S1) and 21% (S2) (5% with at least 3 items)	GoF: NA L: 0.50–0.81 with >0.60 for 15 items (both samples) O: 59% (S1), 61% (S2) of explained variance	With[d]: education, employment, marital status, hypertension, duration of disease
Gensichen Germany Major depression (n = 442) [11]	German PACIC[a]	EFA	2	0.45–0.91	NA	CE: 12.9% (PA),8.9% (PS) FE: 4.6%(GS) M: 0.7–5.4%	GoF: NA L: PA, DS and PS on the first factor. GS and FC on the second factor O: 46.5% of explained variance	With[d]: EUROPEP None[e]: age, gender, education, comorbidities, PHQ9
Goetz Germany Chronic illnesses (n = 264) [12]	German PACIC short form[c]	PCA	1	0.87	NA	CE: 18.1–58.9% with >20% for 9 of 11 items FE: 1.2–43.3% with >20% for 7 of 11 items M: 4.2–12.5%	GoF: NA L: 0.52–0.85 O: 48% of explained variance, KMO = 0.90, Bartlett's test of sphericity: $P < 0.001$	None[e]: comorbidities

(*continued*)

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Appendix I Continued

Author Country Disease(s) targeted (sample size)	PACIC version	Type of analysis	Number of dimensions	Alpha cronbach	Test-retest	Data quality ceiling effect (CE) Floor effect (FE) Missing (M)	Goodness-of-fit (GoF), loadings (L), Other (O)	Associations with other variables
Drewes Netherlands Diabetes (n = 1547) [13]	Dutch PACIC[a]	EFA (polychoric correlation matrix, split half sample) CFA (polychoric correlation matrix, split half sample)	1, 2, 3, 4 and 5 dimensions	0.92	NA	CE: NA FE: NA M: 20% (multiple imputation performed)	GoF: none of the models have acceptable fits: RMSEA > 0.10 GoF of other structures: no acceptable fits L: NA O: EFA, no clear structure	With[d]: age, education and duration of diabetes
Cramm Netherlands CVD (n = 1167) [14]	Dutch PACIC (long/short form)[a]	CFA both on full data and imputed data; test-retest (n = 585)	1	0.88–0.93	NA	CE: NA FE: NA M: 7.9–9.7%, (mean imputation performed)	GoF: acceptable fit L: NA	NA
Rick United-Kingdom Long term conditions (n = 1846) [15]	Original PACIC[a]	CFA both on full data and imputed data	5	0.68–0.94	NA	CE: none FE: 20.9% (PA), 14.2% (GS), 14.7% (PS), 30.4% (FC) M: 9.6–15.9%, 14.6% full PACIC missing (multiple regression imputation performed)	GoF: no acceptable fit L: NA O: Structure not found	With[d]: age, gender, shared decision making, assessment of quality of care, patient satisfaction None[e]: number of conditions, contact with a GP, main professional responsible for care

PACIC original dimensions: PA, patient activation; DS, delivery system; GS, goal setting; PS, problem solving; FC, follow-up and coordination; EFA, exploratory factorial analysis; CFA, confirmatory factorial analysis; PCA, principal component analysis; KMO, Kaiser–Meyer–Olkin test; NA, not available; CE, ceiling effect; FE, floor effect; M, missing data; S1, sample 1; S2, sample 2; HbA1c, glycated hemoglobin; LDL, low-density lipoprotein (cholesterol); EUROPEP, European patient evaluation of general practice care; PHQ9, Patient health Questionnaire; GP, general practitioner; IHD, ischemic heart diseases; COPD, chronic obstructive pulmonary disease; HBP, high blood pressure; CVD, cardio-vascular diseases.

[a]Response scale: from 1: almost never to 5: almost always.

[b]Response scale: from 1: never to 5: always.

[c]11-point scale, from 0 to 100%.

[d]Association shown between PACIC score and the listed variables.

[e]Associations were not detected between PACIC scores and the listed variables.

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