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Clinical Correspondence

Confirming the two factor model of dispositional cancer worry

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Dear Editor,

Recently, Jensen et al. argued that dispositional cancer worry was (a) distinct from dispositional worry and (b) defined by two underlying dimensions: severity and frequency [1]. Worry severity refers to the intensity of the affect whereas worry frequency represents how often cancer-related thoughts occur. Based on exploratory factor analysis, Jensen et al. advocated an eight-item measure with four items for each hypothesized factor. However, the two-factor model (severity and frequency) still needs to be confirmed in additional studies.

The goal of the current manuscript is to evaluate opposing measurement models of dispositional cancer worry (two factors vs. one factor) and to test whether the optimal measurement model is invariant (i.e. holds across studies) [2,3].

Method

Procedure

Data from eight separate studies are utilized in this analysis. Basic details about all studies are provided in Table 1. All procedures were approved by a university IRB.

Measures

Dispositional cancer worry has two hypothesized dimensions: severity and frequency. For all eight studies, four-item scales were used to assess each dimension, per Jensen et al. [1]. Participants responded using a seven-point scale anchored with *not at all* (1) and *very much* (7). The severity items were culled from the brief worry scale (BWS) developed by Dijkstra and Brosschot [4], and the frequency items were taken from the revised impact of event scale (RIES) developed by Weiss and Marmar [5]. Jensen et al. [1] demonstrated that the BWS and RIES were the best representations of the two hypothesized dimensions.

Analysis

Model estimation was carried out using LISREL 8.80. Because the data were non-normal, CFA was carried out using the asymptotic covariance matrix. Thus, a Satorra–Bentler (S–B) χ^2 is reported, which adjusts for non-normal distributions [6]. In addition to the S–B χ^2, which can be sensitive to sample size, five other fit indices were examined: χ^2/df ratio, CFI, RMSEA, SRMR, and Model AIC. The χ^2/df ratio adjusts for sample size by dividing the χ^2 by the degrees of freedom. Ratios around three indicate a good fit to the data [7]. For CFI, conventional standards suggest .95 to indicate good fit [8]. For RMSEA, .08 and lower indicates good fit, while .05 or lower indicates excellent fit [8,9]. The Standardized RMR (SRMR) indicates good fit at .08 or lower [8]. The Model AIC is used to compare different models; lower scores indicate better fit [10].

Results

Approximately 3% of the data were missing and replaced using expectation maximization. All items were significantly skewed and kurtotic (see Table 2). As a set, the items exhibited significant multivariate abnormality, skewness = 29.87, z score = 83.00, $p < .001$, and kurtosis = 153.73, z score = 45.85, $p < .001$. This is not surprising as researchers have long noted that most psychosocial variables are non-normal [11]. The concern is that few researchers adjust their analytic approach to handle non-normal data.

All eight datasets were included in a single, multi-group confirmatory factor analysis (CFA). For comparative purposes, the initial measurement model consisted of one

Table 1. Demographic details for the eight study sample

Study	N	Age (M/SD)	% Female	% Caucasian	% < HS degree	Recruited from:
1	481	36.68 (16.33)	66.20	83.20	41.60	Mall in Midwestern U.S.
2	264	40.58 (12.85)	100.00	75.80	68.50	Mall in Midwestern U.S.
3	205	37.80 (14.20)	100.00	89.30	N/A	OBGYN Practice in Midwestern U.S.
4	209	55.56 (4.24)	71.80	97.10	72.70	8 worksites in Midwest U.S.
5	445	20.00 (1.57)	100.00	71.20	100.00	University in Midwestern U.S.
6	453	20.37 (1.94)	53.40	78.40	100.00	University in Midwestern U.S.
7	348	23.30 (2.16)	100.00	75.00	86.50	Online Panel (46 U.S. states represented)
8	111	44.39 (16.90)	55.70	99.10	59.80	Rural Community in Western U.S.

Note. Total $N = 2516$. % <HS Degree = percent of participants with more than a high school degree.

latent variable (cancer worry) and eight indicators. The one-factor model indicated poor fit, S–B χ^2 (160, $N = 2300) = 5177.81$, $p < .001$, χ^2/df ratio = 32.36, CFI = .76, RMSEA = .33 (90% CI: .32, .34), SRMR = .15, Model AIC = 5433.81 (see Figure 1). Past research has suggested that dispositional cancer worry could have two underlying dimensions: severity and frequency. Thus, a second model was tested with two latent variables (severity and frequency). In line with past research, four items were loaded on the latent variable of severity (DCW01–04), and four items were loaded on frequency (DCW05–08). The two-factor model was superior to the one-factor model, but still failed to achieve good fit, S–B χ^2 (152, $N = 2300) = 728.61$, $p < .001$, χ^2/df ratio = 4.79, CFI = .96, RMSEA = .12 (90% CI: .11, .12), SRMR = .08, Model AIC = 1000.61. Modification indices suggested that the model could be improved by allowing for error-term correlations between several items. Error correlations should only be employed when there is sufficient justification [12], although it has been noted that such modification may be necessary for many models [13]. Two pairs (DCW01, DCW04; DCW05, and DCW07) contain similar language (i.e. 'physical consequences,' 'pictures'), and three items (DCW05–DCW07) are about thoughts popping to mind. Accordingly, error-term correlations were allowed between these items (see final model in Figure 1). The two-factor model with correlated error terms was a good fit for the data, S–B χ^2 (120, $N = 2300) = 331.73$, $p < .001$, χ^2/df ratio = 2.76, CFI = .99, RMSEA = .078 (90% CI: .07, .09), SRMR = .07, Model AIC = 667.73.

Based on fit indices, the two factor model is superior to the one factor model. However, this does not equate to discriminant validity. Discriminant validity is achieved when a latent variable accounts for more variance in corresponding observed variables relative to measurement error and other latent variables in the model [9]. There are several valid approaches to assessing discriminant validity. For the current data, a paired construct test is utilized. In a paired construct test, the parameter estimate between two latent variables is fixed to 1.00, and then the model is re-estimated. If the chi-square for the original model is better than the fixed model by more than 3.84, then there is compelling evidence that discriminant validity has been achieved [14]. The parameter between severity and frequency was fixed to 1.00, resulting in a χ^2 (17) =310.01, $p < .001$. Thus, there is ample evidence of discriminant validity between severity and frequency. Each latent variable accounts for more variance in its observed variables than either error or the other latent variable.

Invariance is established if a measure has consistent structure/loadings across multiple datasets [2,3]. Three

Table 2. Summary statistics for dispositional cancer worry items

		M(SD)	Skewness	Kurtosis
Cancer worry—severity				
DCW01	I am afraid of the physical consequences of getting cancer	4.36 (1.95)	−.15*	−1.13*
DCW02	I worry about my health because of my chances of getting cancer	3.61 (1.89)	.27*	−1.00*
DCW03	I feel anxiety when I think of the possible consequences of getting cancer	3.69 (1.92)	.21*	−1.05*
DCW04	I brood about the physical consequences of getting cancer	2.87 (1.77)	.70*	−.48*
Cancer worry—frequency				
DCW05	Pictures about cancer popped into my mind	1.57 (1.20)	2.54*	6.50*
DCW06	I had dreams about cancer	1.67 (1.21)	2.13*	4.44*
DCW07	I had waves of strong feelings about cancer	1.49 (1.13)	2.81*	8.17*
DCW08	I had trouble falling asleep or staying asleep, because pictures or thoughts about cancer that came to mind	1.56 (1.56)	2.50*	6.50*

Note. Summary statistics for DCW items across all 8 studies. Response options for all items are *not at all* to *very much* measured on a 7 pt. scale.
*$p < .05$

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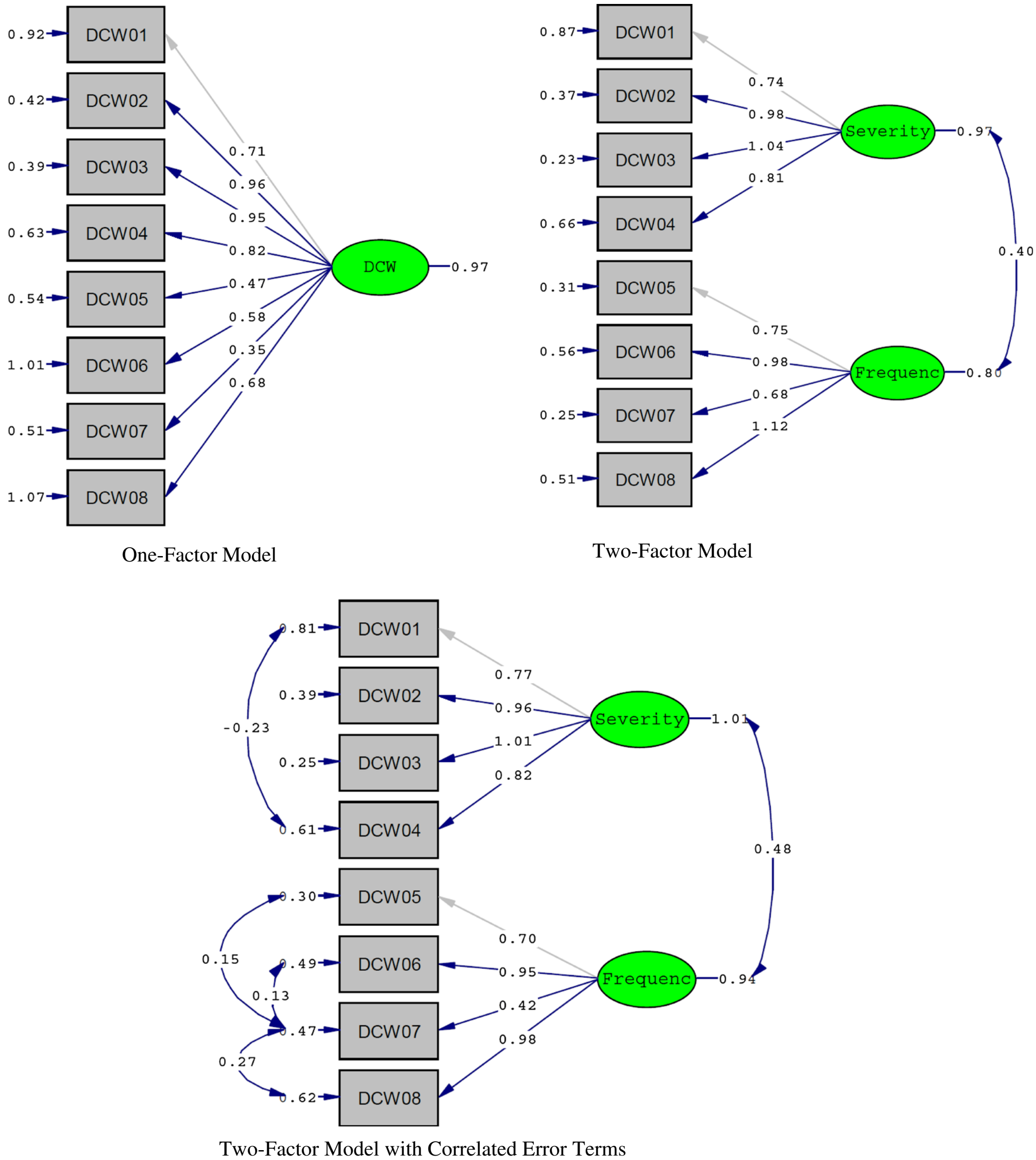

Figure 1. Confirmatory factor analyses testing three possible models of dispositional cancer worry (across eight datasets). The two-factor model with correlated error terms exhibited the best Model AIC = 667.73

forms of invariance were tested (configural, metric, and scalar). The two factor model exhibited configural invariance, but fell short of metric or scalar invariance (see Table 3). That means that researchers can assume that different study populations should perceive the two factor structure (severity and frequency). However, researchers should not assume that relationships between latent and observed constructs will be identical (scalar invariance)

Table 3. Fit indices for invariance tests

Model	X^2 (df)	X^2/df	RMSEA	SRMR	CFI	AIC	Decision
Configural	331.73 (120)	2.76	.08	.073	.99	667.73	Accept
Metric	3502.17 (267)	13.12	.21	.26	.76	3544.17	Reject
Scalar	4357.59 (309)	14.10	.21	.25	.71	4443.59	Reject

Note. Models can be directly compared via the AIC score (lower score, better fit). The overall fit of the model can be assessed using the chi-square/degrees of freedom ratio (X^2/df), RMSEA, SRMR, and CFI. Based on these criteria, only the configural model is an adequate fit for the data. Configural invariance establishes that the basic model structure is invariant; that is, participants from different studies conceptualize the constructs the same.

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or that the intercepts will be identical across samples (scalar invariance). In practical terms, this means that scholars should not compare scores across samples [3].

Based on these analyses, two scales were created. Afraid, worry, anxiety, and brood were combined into a four item measure of cancer worry—severity (CWS), which exhibited high internal consistency ($M = 3.63$, $SD = 1.65$, alpha = .90). Pictures, dreams, waves, and sleeping were combined into a four item measure of cancer worry—frequency (CWF), which also exhibited high internal consistency ($M = 1.57$, $SD = .95$, alpha = .83).

Discussion

Analysis of data from eight studies supported the two-factor model of dispositional cancer worry identified by Jensen et al. [1]. This suggests that single-item measures may not fully capture the complex nature of the construct [15]. It also suggests that dispositional cancer worry and dispositional worry may have similar factor structures. This might lead some to question whether the two constructs are distinct. Jensen et al. [1] found preliminary evidence that the two constructs diverged, though future research should continue to explore this possibility.

Disciplined measurement research is never really finished as it is always possible to use the current measure to develop new, superior psychometric approaches [15]. The CWS and CWF provide researchers and practitioners with an eight-item measure that consistently captures the two hypothesized dimensions of dispositional cancer worry, and diverges from dispositional worry. Future work should examine how these instruments perform over time, whether they can predict variance in key cognitive/behavioral outcomes, and factors that influence their development.

Key points

- Confirmatory factor analysis was utilized to analyze data from eight studies that measured dispositional cancer worry.
- In study 1, a two-factor model of dispositional cancer worry was superior to a one-factor model.
- The two-factor measurement model was replicated across eight studies.
- Dispositional cancer worry has two underlying factors: severity and frequency.
- Two four-item measures effectively capture both dimensions.

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