A bifactor model of intolerance of uncertainty in undergraduate and clinical samples: Do we need to reconsider the two-factor model?

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Abstract

The theorized role that intolerance of uncertainty (IU) plays in the acquisition, maintenance, and treatment of multiple emotional disorders underscores the importance of valid assessment tools. Research using the Intolerance of Uncertainty Scale-Short form (IUS-12) has conceptualized IU along two dimensions, namely, prospective IU and inhibitory IU. However, recent research has cast doubt on the separability of these dimensions. The aim of the current study was to evaluate the fit of competing measurement models of the IUS-12 in separate undergraduate (N = 506) and clinical (N = 524) samples. Unidimensional, correlated two-factor, and bifactor models were tested using confirmatory factor analysis. The results of both studies supported a bifactor model consisting of a strong general IU factor. The general IU factor explained the majority of unique variance in the IUS-12, and suggested that a total score is generally appropriate for assessing IU. The general IU factor was most strongly and consistently associated with symptoms of multiple disorders. The inhibitory IU group factor was more weakly associated with most symptom measures in the clinical sample, but only with social phobia symptoms in the undergraduate sample. The prospective IU group factor was only separable from the general IU factor in the undergraduate sample, and did not explain unique variance in disorder symptoms.

Public Significance Statement: The present study supports a bifactor model of the Intolerance of Uncertainty Scale-Short Form, and suggests that the total score is generally appropriate for assessing intolerance of uncertainty (IU) in undergraduate and clinical samples. Additionally, it highlights the relative contributions of general, prospective (cognitive), and inhibitory (behavioral) aspects of IU to symptoms of emotional disorders.

Keywords: intolerance of uncertainty, IUS-12, confirmatory factor analysis, bifactor model, psychometrics, measurement, assessment

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Intolerance of uncertainty (IU) is a dispositional trait that reflects a fear of the unknown and an "incapacity to endure the aversive response triggered by the perceived absence of salient, key, or sufficient information, and sustained by the associated perception of uncertainty" (Carleton, 2016, p. 31). IU is posited to be central to psychopathology as difficulty tolerating uncertainty may contribute to maladaptive cognitions (e.g., worry) and behaviors (e.g., avoidance) evident in emotional disorders (Boswell, Thompson-Hollands, Farchione, & Barlow, 2013; Carleton, 2016). These maladaptive cognitive and behavioral processes may reflect attempts to alleviate uncertainty and increase control and, as such, engagement in such strategies perpetuates IU and associated emotional distress and anxiety (Boswell et al., 2013).

A substantial body of research suggests that IU is a robust transdiagnostic risk factor associated with multiple types of psychopathology (e.g., anxiety, mood, and eating disorders; Carleton, 2012; Hong & Cheung, 2015; Mahoney & McEvoy, 2012b; Renjan, McEvoy, Handley, & Fursland, 2016; Shihata, McEvoy, Mullan, & Carleton, 2016). As such, IU has been conceptualized as a generalized underlying mechanism for anxious pathology and a core feature in anxiety-related experience (Boswell et al., 2013; Carleton, 2016; Harvey, Watkins, Mansell, & Shafran, 2004). IU has been implicated as a potentially critical transdiagnostic treatment target. Treatment protocols that directly and indirectly target IU have been supported as efficacious, resulting in symptom reduction and clinically significant change (Dugas & Robichaud, 2007; McEvoy & Erceg-Hurn, 2016; van der Heiden, Muris, & van der Molen, 2012). Moreover, changes in IU may contribute to changes in disorder symptoms across different clinical

interventions, suggesting that IU is transdiagnostic and transtherapeutic in nature (McEvoy & Erceg-Hurn, 2016; Treanor, Erisman, Salters-Pedneault, Roemer, & Orsillo, 2011).

The role IU is theorized to play in the development, maintenance, and treatment of multiple emotional disorders highlights the importance of valid measures of IU. Over the last two decades there has been an increasing interest in IU, which has been accompanied by the development of a number of self-report measures designed to assess IU. Psychometric research on the first measure of IU, the 27-item IU Scale (IUS), provided initial evidence of construct validity, and internal and test-retest reliability of the total score (Freeston, Rhéaume, Letarte, Dugas, & Ladouceur, 1994). However, inconsistencies with the factor structure and length of the IUS, as well as suggestions of potential redundancy amongst items (Carleton, Norton, & Asmundson, 2007; McEvoy & Mahoney, 2011; Norton, 2005), led to the development of the revised 12-item IUS, Short Form (IUS-12; Carleton et al., 2007). The IUS-12 demonstrated strong psychometric properties and a high correlation with the original IUS (r = .96). Measurement research suggests that the IUS-12 consists of two highly correlated and replicable factors that yield two subscales: a 7-item prospective IU subscale assessing desire for predictability and cognitive appraisals about future uncertainty, and a 5-item inhibitory IU subscale assessing behavioural inhibition or avoidance when faced with uncertainty. The IUS-12 total and subscale scores have showed good construct validity, internal reliability (Cronbach's α of .91 for the total scale and .85 for both subscale scores), and test-retest reliability over a two-week interval (r = .77, Carleton et al., 2007; Khawaja & Yu, 2010).

Prior research investigating IU has computed either the IUS-12 total score, the prospective IU and inhibitory IU subscale scores, or both the total and subscale scores (Carleton, Fetzner, Hackl, & McEvoy, 2013; Carleton, Mulvogue, et al., 2012; Mahoney & McEvoy,

2012b). Differential associations have been found between prospective and inhibitory IU and symptoms of emotional disorders, such that prospective IU appears to be more strongly related to generalized anxiety disorder and obsessive-compulsive disorder, whereas inhibitory IU appears to be more strongly related to symptoms of social anxiety, panic disorder, depression, and posttraumatic stress disorder (Boelen, Reijntjes, & Smid, 2016; Mahoney & McEvoy, 2012a; McEvoy & Mahoney, 2011). Given the relatively recent conceptualization of these subscales there is limited research and the results are not entirely consistent. Moreover, recent research has begun to question the separability of these subscales (Hale et al., 2016; Lauriola, Mosca, & Carleton, 2016).

The different approaches to using the IUS-12 (i.e., computing subscale versus total scores) are based on the underlying assumptions that the prospective and inhibitory IU subscales reflect theoretically distinct constructs beyond the total scale, and/or that each subscale reflects the same general IU construct (Reise, Bonifay, & Haviland, 2013). Reise, Moore, and Haviland (2010) assert that a correlated-traits model and differential relations between subscales and external variables do not provide sufficient evidence for estimating subscale scores. Rodriguez, Reise, and Haviland, (2016, p. 234) assert that “differential correlates are the expectation” as any subscales that are not perfectly correlated will have differential predictive utility because each subscale is a combination of the underlying general factor and a separate group factor (Reise et al., 2010). Moreover, the multidimensionality present in the data may impact the interpretability of the total score, and the apparent reliability of the subscales or narrow dimensional traits may be a reflection of a more general trait IU (Reise et al., 2010). Without empirical justification, interpreting subscale scores as reflecting a meaningful latent construct distinct from a general IU factor may be misguided (Rodriguez et al., 2016). In line with this, Hale et al. (2016) asserted

that the computation and interpretation of the prospective IU and inhibitory IU subscale scores in past research was not psychometrically justified. Bifactor modelling is one option for assessing the assumptions that the multidimensional IUS-12 subscales capture unique variance after accounting for the total scale, or alternatively that they reflect a single underlying construct (Reise et al., 2010). Bifactor models, which retain a general factor but also recognize the multidimensionality caused by group factors, are becoming increasingly applied to psychological and clinical constructs (see Reise et al., 2010, for a comprehensive review). Adopting a bifactor approach can inform researchers and clinicians on the psychometric structure of a measure, including the properties of total and subscale scores (and whether total and/or subscale scores should be computed), as well as how a measure should be modelled in structural equation modelling (SEM; Reise et al., 2013; Reise et al., 2010).

Only two studies to date have tested a bifactor model using the IUS-12. Hale et al. (2016) compared unidimensional, two-factor correlated traits, and bifactor models in an undergraduate sample. Results revealed that the bifactor model yielded the best fit to the data, indicating the presence of a strong general IU factor with substantially higher reliability and that explained a greater proportion of shared variance (80%) than the prospective and inhibitory IU group factors. Similarly, Lauriola et al. (2016) compared unidimensional, two-factor, second-order hierarchical, and bifactor models of the IUS-12 (Italian translation) using an undergraduate sample. Consistent with Hale et al.'s (2016) findings, Lauriola et al. (2016) found the bifactor model exhibited superior fit, and the general IU factor was more reliable and explained a greater amount of common variance (75%) than either group factor. Therefore, despite past studies reporting results using both IUS-12 total and subscale scores (Mahoney & McEvoy, 2012a; McEvoy & Mahoney,

2011), both Hale et al. (2016) and Lauriola et al. (2016) recommended computing only IUS-12 total scores and suggested the IUS-12 has a predominantly unidimensional structure.

While this research appears to support bifactor models of the IUS-12, it is limited to only one study using the English version in an undergraduate sample and none in a clinical population. It is plausible that prospective IU and inhibitory IU are more differentiated at clinical than non-clinical levels of psychopathology. For instance, at clinical levels of anxiety there is evidence that neural structures such as the amygdala are more strongly activated and therefore play a greater role in identifying and focusing attention on perceived threats in states of uncertainty (general IU), and the insula plays a greater role in prospective IU by guiding predictions about subjective feelings of future events (Wever, Smeets, & Sternheim, 2015). In contrast, hyperactivation of the amygdala, in conjunction with *hypo*activation of neural structures that inhibit the freeze response (e.g., ventromedial prefrontal cortex), may contribute to inhibitory IU (Grupe & Nitschke, 2013). Further research investigating bifactor models are therefore required to determine if the initial findings of a predominant common factor in undergraduates is replicated in clinical samples, or rather whether the group factors are more separable and provide unique predictive utility in a clinical sample.

Improving understanding of the structure of the IUS-12 is also important due to its recent inclusion as a key behavioral assessment method of potential threat (Negative Valence System) in the National Institute of Mental Health's Research Domain Criteria (RDoC) initiative (National Institute of Mental Health [NIMH], 2016). The aim of the RDoC initiative is to identify transdiagnostic, dimensional constructs reflecting the core mechanisms of psychopathology across units of analysis (e.g., neural circuitry, physiology, genes, self-report) as an alternative to categorical nomenclature (Berenbaum, 2013; Shankman & Gorka, 2015).

Moreover, the transdiagnostic and transtherapeutic relevance of IU to psychopathology underscores the importance of valid measures and research that informs the scoring and interpretation of the IUS-12.

The aim of the present study was to use bifactor modelling to elucidate the extent to which the IUS-12 yields a total score in undergraduate and clinical samples, and thus whether scoring the prospective IU and inhibitory IU subscales is psychometrically justified, and to inform how the IUS-12 should be used in structural models that examine IU (Reise et al., 2013; Rodriguez et al., 2016). The first hypothesis was that a bifactor model would provide the best fit relative to the unidimensional and two-factor correlated models in an undergraduate sample, and that most variance in the IUS-12 would be explained by the general IU factor, thereby replicating Hale et al. (2016) and Lauriola et al.'s (2016) findings. We extended this previous research to a clinical sample with anxiety and depressive disorders. It was possible that the findings from the undergraduate sample would be replicated. However, it was also plausible that the prospective IU and inhibitory IU group factors would be more separable from the general factor at clinical levels of anxiety, and that these group factors would explain a substantial proportion of reliable variance in the IUS-12. The second hypothesis was that the general IU factor would be a strong predictor of symptoms of multiple emotional disorders in both the undergraduate and clinical samples. If the group factors are found to be separable in the clinical sample, it would be expected that they will explain unique variance in symptoms beyond the general factor.

Method

Participants and Procedure

Undergraduate Sample. Participants (N = 506) were undergraduate psychology students aged between 18 and 55 (M = 21.00; SD = 4.91; 80% female). Participants were recruited via the

university's research participant pool through an online experiment database and completed the questionnaire battery online at their convenience. Participants read an information statement and were then directed to an online survey hosted by Qualtrics, where they completed demographic information and the IUS-12 along with a battery of standardized self-report measures used as part of a larger study (Shihata, McEvoy, & Mullan, 2017). Informed consent was obtained from all participants. The IUS-12 was presented first followed by the Disorder-Specific IU Scale (Thibodeau et al., 2015; data not reported here) with the remaining questionnaires randomized. Participants were debriefed and received course credit for their participation. Institutional ethics approval was obtained prior to the commencement of this study (HR34/2015-2).

Clinical Sample. Participants (N = 524) were referred by health professionals to a specialist service for the treatment of anxiety and/or depressive disorders. Prior to the initial assessment session participants were posted a standard questionnaire battery that was completed and brought to the initial assessment. At the initial assessment participants were diagnosed via a structured diagnostic interview (Mini International Diagnostic Interview; Sheehan et al., 1998) administered by a masters- or doctorate-level Clinical Psychologist. Inclusion criteria for this study was a principal Diagnostic and Statistical Manual for Mental Disorders (DSM-IV; American Psychiatric Association, 1994) anxiety or depressive disorder (major depressive disorder or dysthymia). Participants were aged between 18 and 69 (M = 33.67; SD = 12.24; 66% female). The proportion of participants meeting criteria for principal anxiety and depressive disorders were as follows; social phobia (n =144), generalized anxiety disorder (n = 101), panic disorder with or without agoraphobia (n = 21), specific phobia (n = 7), major depressive disorder (current and in partial remission; n = 222), dysthymic disorder (n =19), anxiety disorder not otherwise specified (n = 8), and depressive disorder not otherwise specified (n = 2). A total of

27% of the sample met criteria for having one diagnosis, 43% had two diagnoses, and 30% had three or more diagnoses. Data on education and marital status were available for 483 participants, with 51% employed, 32% with a university education qualification, 13% with a technical or trade certificate, and 55% who completed high school or less. Half of the sample were single (55%), with the remaining 34% either married or with a live in partner, and 10% either widowed, separated, or divorced.

Measures

Undergraduate Sample.

Intolerance of Uncertainty Scale, Short Form (IUS-12; Carleton et al., 2007). The IUS-12 was developed to measure negative beliefs about and reactions to uncertainty. Participants responded to each item on a five-point scale from *not at all characteristic of me* (1) to *entirely characteristic of me* (5). The IUS-12 total and subscale scores have demonstrated strong psychometric properties including good internal and test-retest reliability and construct validity in diverse populations (Carleton et al., 2007; Khawaja & Yu, 2010; McEvoy & Mahoney, 2011).

Generalized Anxiety Disorder-7 (GAD-7; Spitzer, Kroenke, Williams, & Löwe, 2006). The GAD-7 was designed to assess the severity of symptoms of generalized anxiety disorder. Participants indicated how often, in the last two weeks, they felt bothered by a range of symptoms along a four-point scale ranging from *not at all* (0) to *nearly every day* (3). Psychometric support indicates evidence of good reliability, construct, discriminant, and factorial validity (Carleton, Mulvogue et al., 2012; Löwe et al., 2008).

Social Interaction Phobia Scale (SIPS; Carleton et al., 2009). The 14-item SIPS measures symptoms of social phobia including cognitive, emotional, and behavioral reactions to social interactions (Carleton et al., 2009). Participants responded to each item by indicating the

extent to which they were bothered by symptoms along a five-point scale ranging from *not at all characteristic of me* (0) to *extremely characteristic of me* (4). Previous research has supported a three-factor model wherein each subscale assesses a different dimension of social anxiety (social interaction anxiety, fear of overt evaluation, and fear of attracting attention). The SIPS total and subscale scores have demonstrated excellent reliability in both clinical and non-clinical samples and strong factorial, convergent, and discriminant validity (Carleton et al., 2009; Menatti et al., 2015).

Panic Disorder Severity Scale-Self-Report (PDSS-SR; Houck, Spiegel, Shear, & Rucci, 2002). The 5-item PDSS-SR assesses the severity of panic disorder symptoms. Participants responded to each item by indicating the frequency, distress, and avoidance behaviors associated with panic attacks along a five-point scale ranging from *none* (0) to *extreme* (4). Psychometric evidence indicates acceptable validity and internal reliability (Houck et al., 2002; Wuyek, Antony, & McCabe, 2011).

Clinical Sample.

IUS-12 (Carleton et al., 2007). As described above.

Beck Anxiety Inventory (BAI; Beck, Epstein, Brown, & Steer, 1988). The widely used 21-item BAI was designed to assess subjective, neurophysiologic, autonomic, and panic-related symptoms of anxiety. Participants indicated the extent to which they felt bothered by a range of symptoms during the past week along a four-point scale ranging from *not at all* (0) to *severely – I could barely stand it* (3). Psychometric support indicates evidence of good reliability and validity (Beck et al., 1988).

Beck Depression Inventory-II (BDI-II; Beck, Steer, & Brown, 1996). The 21-item BDI-II is a widely used instrument designed to measure the severity of depressive symptoms during

the previous two weeks. Participants responded to each item and statement group along a four-point scale from *symptom not present* (0) to *very intense* (3). Although prior studies have reported equivocal factor structures, recent psychometric research suggests computing a total score (Brouwer, Meijer, & Zevalkink, 2012). Psychometric evidence indicates the BDI-II has good construct validity and high internal and test-retest reliability (Beck et al., 1996; Storch, Roberti, & Roth, 2004).

Penn State Worry Questionnaire (PSWQ; Meyer, Miller, Metzger, & Borkovec, 1990). The 16-item PSWQ is a widely used measure of pathological worry. Participants responded to each item statement on a five-point scale ranging from *not at all typical of me* (1) to *very typical of me* (5). The PSWQ has demonstrated high internal and test-retest reliability and good construct validity in clinical and non-clinical populations (Brown, Antony, & Barlow, 1992; Meyer et al., 1990).

Social Interaction Anxiety Scale (SIAS; Mattick & Clarke, 1998). The 20-item SIAS was designed to assess anxiety symptoms including cognitive, behavioral, and affective reactions associated with social interactions. Participants responded to items on a five-point scale ranging from *not at all characteristic or true of me* (0) to *extremely characteristic or true of me* (4). The SIAS total score has demonstrated evidence of good reliability as well as convergent and discriminant validity (Mattick & Clarke, 1998).

Data Analysis

Preliminary data screening of distributions, skewness, and kurtosis were performed in SPSS 22.0.

Measurement Models and Evaluation. Confirmatory factor analysis (CFA) using mean- and variance-adjusted weighted least squares (WLSMV) estimation was conducted in Mplus 7.4

(Muthén & Muthén, 1998-2015) to assess the relative fit of the competing IUS-12 measurement models. The use of WLSMV estimation is appropriate as the item responses of the IUS-12 are ordered-categorical data (Brown, 2006). This approach is consistent with the WLSMV estimation procedure used in previous bifactor studies on the IUS-12 (Hale et al., 2016) and other anxiety-related measures (Ebesutani, McLeish, Luberto, Young, & Maack, 2014; Fergus & Bardeen, 2017). The IUS-12 bifactor model was tested against a unidimensional and two-factor correlated model mirroring extant studies (Hale et al., 2016; Lauriola et al., 2016), and to evaluate whether each of these models would demonstrate comparable fits in our samples. The unidimensional model consisted of each of the IUS-12 items loading onto a single latent factor. The two-factor correlated model consisted of seven items with loadings on a prospective IU group factor and five items with loadings on an inhibitory IU group factor, as reported by Carleton et al. (2007). The bifactor model consisted of all 12 items loading on a general IU factor as well as on their specific group factor. Consistent with Hale et al. (2016), the covariances of all of the factors were fixed to zero.

A number of fit indices were examined to evaluate the fit of competing models including the chi-square goodness of fit statistic (χ^2), where a non-significant value suggests an acceptable fit. However, the chi-square statistic is influenced by sample size and in large samples often rejects the model (Tabachnick & Fidell, 2013). Additional fit indices included the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the root mean square error of approximation (RMSEA) with 90% confidence intervals (CIs). For the CFI and TLI, values greater than .90 and .95 indicate an acceptable and excellent fit, respectively (Hu & Bentler, 1999; Marsh, Hau, & Wen, 2004). For the RMSEA values close to .08 and .06 indicate an acceptable fit (lower values correspond with closer fit) and the upper CI limit should not exceed .10 (Hu & Bentler,

1999; Kline, 2016; Marsh et al., 2004). Model comparisons were evaluated using chi-square difference tests (using the DIFFTEST function in Mplus; Muthén & Muthén, 1998-2015).

Bifactor Model and Evaluation. Consistent with a bifactor model-based approach, a number of other statistical indices were calculated to better inform the psychometric properties of the total and subscale scores and use of the IUS-12 as a latent variable in SEM (see Rodriguez et al., 2016 for review). Coefficient omega (ω) and omega subscale (ω_S) is a model-based estimate of internal reliability that can be applied to both the general factor and group factors, respectively. The coefficient omega represents the proportion of variance in raw scores for the total scale and each subscale that is explained by all sources of common variance (i.e., both the general factor and each group factor). Omega hierarchical (omegaH or ω_H) represents the proportion of variance in IUS-12 total scores that is explained by the general factor. Omega hierarchical subscale (omegaHS or ω_{HS}) represents the reliability of a subscale score (or the unique variance of each group factor) after controlling for the variance accounted for by the general factor (Reise et al., 2013). Construct replicability (*H*) represents the quality of an item set or indicators and the reproducibility of a latent variable, and thus, its use in an SEM measurement model (Rodriguez et al., 2016). A high *H* value (greater than .70; Hancock & Mueller, 2001) suggests a well-defined latent variable, which is likely to be stable and replicable, whereas a low *H* value indicates a poorly defined variable, which is likely to change across studies.

Explained common variance (ECV) and percent uncontaminated correlations (PUC) are indices that inform whether a bifactor structure with a strong general factor should be modelled as a unidimensional or multidimensional (bifactor) measurement model in SEM. ECV reflects the proportion of all common variance explained by the general factor relative to the group

factors (Rodriguez et al., 2016). A high ECV value (greater than .70 or .80; Rodriguez et al., 2016) lends support for a strong general factor as well as the unidimensionality of a scale's items. In addition, item-explained common variance (I-ECV) represents the proportion of common variance for each IUS-12 item accounted for by the general factor. For the I-ECV, values greater than .80 typically suggest that the IUS-12 items primarily reflect the general factor relative to the group factor and represent a unidimensional item set (Stucky & Edelen, 2015). The ECV is useful to interpret alongside the PUC, which reflects the percent of IUS-12 item covariances influenced by the variance explained by the general factor and group factors (Rodriguez et al., 2016). Thus, the higher the PUC, the more the correlation matrix reflects the general factor (Rodriguez et al., 2016). Parameter bias less than 10% to 15% is considered acceptable, and as such, does not present a serious concern (Muthén, Kaplan, & Hollis, 1987). Moreover, Reise, Schienes, Widaman, and Haviland (2013, p. 22) state that when omegaH values for the general factor are greater than .70, ECV values are greater than .60, and PUC values are lower than .80, then the multidimensionality in the data is "not severe enough" to impact modelling and interpretation of the IUS-12 as a largely unidimensional measure.

Structural Model. CFA was also used to assess the measurement models of each other measure to be used in the structural model (see Supplementary Material). A structural model was used to assess the incremental validity of the group factor's beyond the general IU factor to symptoms of multiple emotional disorders in the undergraduate (GAD-7, PDSS-SR, SIPS) and clinical sample (BAI, BDI-II, PSWQ, SIAS). Standardized beta estimates were used to examine the strength of the pathways in both samples.

Results

Preliminary Analyses

Scale total scores for the student and clinical samples were normally distributed as evidenced by acceptable skewness (< 2) and kurtosis (<7) levels (Tabachnick & Fidell, 2013). Using Mahalanobis Distance, no influential multivariate outliers were identified. Multicollinearity was not a problem. Descriptive statistics, internal reliabilities (Cronbach's α), and bivariate correlations for the undergraduate and clinical samples are reported in Table 1.

[Table 1 near here]

IUS-12 Measurement Models

The goodness-of-fit statistics for the measurement models tested in the undergraduate sample and clinical sample are displayed in Table 2. In the student and clinical samples, the unidimensional model and the two-factor correlated model provided a marginal fit. The CFI and TLI values met specified guidelines; however, the RMSEA was elevated. A unidimensional model is nested in a two-factor correlated model (Reise et al., 2010), and, as such, the two-factor correlated model was found to fit the data significantly better than the unidimensional model as indicated by a significant chi-square difference. With the exception of a significant chi-square value, the bifactor model, which consisted of a prospective IU and inhibitory IU group factor, displayed a good fit to the data in the undergraduate sample. Although the RMSEA was slightly high, the upper limit of the RMSEA did not exceed .10. A significant chi-square difference indicated that the bifactor model fit the data significantly better than the correlated two-factor model. Although the bifactor model was characterized by a prospective IU and inhibitory IU group factor, it is important to note that the prospective IU group factor was marked by a single

strong loading item (.94) with the other items on this group factor demonstrating relatively low loadings (-.03 to .18).

[Table 2 near here]

In the clinical sample, the bifactor model did not produce an admissible solution and it included negative residual variances, and is therefore not presented here. The model indicated that there was a problem involving the prospective IU group factor. The specific problems were explored and minor modifications were made including fixing residual variances to zero for various combinations of problematic items with negative standardized loadings and removing specific indicators based on non-significant loadings. All of these modifications continued to produce inadmissible solutions. Thus, the bifactor model was modified by removing the prospective IU group factor, which yielded an admissible bifactor model consisting of a general factor and the inhibitory IU group factor that provided a good model fit. The bifactor model fit the data significantly better than the competing two-factor correlated model as indicated by a significant chi-square difference. The standardized factor loadings for the one-factor, two-factor correlated, and bifactor models are presented in Tables 3 (undergraduate sample) and 4 (clinical sample).

[Table 3 near here]

[Table 4 near here]

Evaluation of the IUS-12 through a Bifactor Model Framework

In the undergraduate and clinical samples, most of the IUS-12 items displayed statistically significant and stronger loadings on the general factor than on the group factors. Higher loadings (>.05) on the general factor suggests that the items primarily represent the general IU construct and suggests against computing the subscale scores (Reise et al., 2010).

Omega Reliability Coefficients. In the student and clinical sample, the omega coefficients for the general IU factor and group factors were high. Inspection of omegaH suggested that in both samples 90% of the variance in IUS-12 total scores can be explained by individual differences on the general factor. A comparison between omegaH and omega provides further support that the general IU factor explained a large proportion of variance in total scores (ω_H/ω; .90/.95 = 95%). Moreover, the multidimensionality resulting from the group factors (prospective IU and inhibitory IU in the undergraduate sample; inhibitory IU in the clinical sample) was found to explain only 5% (ω-ω_H; .95-.90) of the variance in IUS-12 total scores. Thus, despite the presence of some multidimensionality, IUS-12 total scores can be practically considered to be a unidimensional representation of trait IU. As can be seen in Table 3 and Table 4, OmegaH for the group factors were low, particularly when compared to their corresponding coefficient omega values. These results suggest that (a) the general IU factor represents the dominant source of variance in the total IUS-12 score, (b) much of the reliable variance in the subscale scores was explained by the general IU factor, (c) there is only a small proportion of common variance remaining after controlling for the general factor, and therefore, (d) the low reliability of the prospective IU and inhibitory IU group factors provides support against their scoring and interpretation.

Construct Replicability. In both samples, the low *H* value of the inhibitory IU group factor suggests that it is a poorly defined and unstable latent variable that is likely to be difficult to interpret within an SEM context. In contrast, the high *H* values of the general factor suggests that it is a well-defined, stable, and replicable latent variable. The results also suggest that researchers can have confidence in the predictive utility of the general IU factor when estimating its relationships with external variables in a structural model. In the undergraduate sample, the

prospective IU group factor also displayed a high *H* value, however, it is important to note that *H* values are disproportionately influenced by items with high factor loadings (Rodriguez et al., 2016). Most items on the prospective IU group factor displayed low loadings with the exception of item 2 (.94), which may have caused the high construct replicability estimate (see Table 3). Therefore, the construct replicability of the prospective IU group factor may be misleading and it may not represent a meaningful or empirically identifiable latent construct.

ECV and PUC. In the student sample, the general IU factor explained 80% of the common variance, whereas 20% of the common variance was shared amongst the prospective and inhibitory IU group factors. Similarly, in the clinical sample, the general factor explained 86% of the common variance, whereas 14% of the common variance was shared with the inhibitory IU group factor. The high ECV values provided support for a strong general IU factor and the unidimensionality of the IUS-12 items. Of the IUS-12 items, 67% (undergraduate) and 75% (clinical) had I-ECV values greater than .80. The average I-ECV value was .85 (range .27 to 1.00) and .89 (range .42 to 1.00) in the undergraduate and clinical samples, respectively, with only three items with I-ECV values lower than .80 (item 2, 6, 7 in the undergraduate sample; items 6, 7, 10 in the clinical sample). Most of the IUS-12 items had high I-ECV values indicating that these items are stronger indicators of general IU and contribute substantially less to the measurement of their respective group factors.

In the undergraduate sample, the PUC value indicated that the general IU factor accounted for approximately half of the item correlations of the IUS-12. In the clinical sample, the PUC value indicated that the general factor accounted for the majority of the IUS-12 item correlations. The average relative parameter bias was acceptable (5% and 8% across IUS-12 items in the undergraduate and clinical samples, respectively) indicating that despite the poorer

fit of the unidimensional model, the presence of some multidimensionality in the data will not introduce problematic levels of parameter bias when modelling the IUS-12 as unidimensional in an SEM framework (Muthén et al., 1987; Rodriguez et al., 2016).

Structural Regression Model

Undergraduate Sample. The final bifactor models were used in all structural models. Standardized beta estimates from the structural regression models are reported in Table 5. The structural model provided an excellent fit to the data, χ^2 (624) =1161.473, $p < .001$, CFI = .985, TLI = .983, and RMSEA = .041 (90% CI [.038 to .045]). The general IU factor was significantly associated with generalized anxiety disorder and panic disorder symptoms; however, the prospective IU and inhibitory IU group factors were not (see Table 5). The general IU factor and inhibitory IU group factor were also significantly associated with symptoms of social phobia. The model explained 47% (R^2) of the variance in symptoms of generalized anxiety disorder, 52% in fear of attracting attention, 44% in fear of overt evaluation, 39% in social interaction anxiety, and 33% in panic disorder.[1]

Clinical Sample. The structural model provided an acceptable fit to the data, χ^2 (3879) = 6643.759, $p < .001$, CFI = .929, TLI = .927, and RMSEA = .037 (90% CI [.035 to .038]). The general IU factor and inhibitory IU group factor were significantly associated with symptoms of anxiety, depression, and social anxiety. As can be seen in Table 5, the general IU factor, but not the inhibitory IU group factor, was significantly associated with worry symptoms. The model explained 41% (R^2) of the variance in pathological worry, 26% in anxiety, and 21% in depression and social anxiety symptoms.

[Table 5 near here].

Discussion

IU is becoming increasingly recognized as a robust transdiagnostic cognitive vulnerability in the conceptualization and treatment of psychopathology (NIMH, 2016). The IUS-12 has become a widely used measure with strong psychometric properties and is considered a viable transdiagnostic assessment tool (Carleton et al., 2007; Khawaja & Yu, 2010). However, bifactor models have recently been investigated in undergraduate samples as alternatives to the previously established two-factor correlated model, which has important implications for the computation of total versus subscale scores (Hale et al., 2016; Lauriola et al., 2016). The present study replicated and extended this research by examining the structure and predictive validity of the IUS-12 across both undergraduate and treatment-seeking clinical samples.

The correlated two-factor model reported in previous studies was replicated in both the undergraduate and treatment-seeking samples. Also consistent with previous research, the bifactor model provided a superior fit (Hale et al., 2016; Lauriola et al., 2016), although there were important differences across the samples. In the undergraduate sample the IUS-12 bifactor model consisted of a general IU factor and two group factors (prospective IU and inhibitory IU), whereas in the treatment-seeking sample, the bifactor model consisted of a general IU factor and only one group factor (inhibitory IU). Although the prospective IU group factor emerged in the undergraduate sample, it did not appear to be a strong factor as evidenced by its low reliability and that most of the items demonstrated low loadings, with the exception of the very high loading of item 2. Thus, the results suggest that in both samples, the structure of the IUS-12 was primarily characterized by a general IU factor and an inhibitory IU group factor. The overwhelming majority of the variance in the IUS-12 scores was attributed to the general IU

factor in both the undergraduate (80%) and clinical (86%) samples. These results are consistent with the findings of two recently published studies with undergraduate samples that reported that the general IU factor explained approximately 80% (Hale et al., 2016) and 75% (Lauriola et al., 2016) of the shared variance in IUS-12 scores. Further, the majority of the reliable variance in the prospective and inhibitory IU subscale scores was found to be explained by the general IU factor.

In both the undergraduate and clinical samples, the general IU factor was most strongly and consistently associated with emotional disorder symptoms. In the student sample, the prospective IU group factor was not significantly associated with any assessed symptoms of emotional disorder. Moreover, the inhibitory IU group factor was only uniquely, although more weakly, associated with symptoms of social phobia. In the clinical sample, the inhibitory IU group factor was also most strongly associated with social anxiety symptoms, but also more weakly with anxiety and depression, which is consistent with previous research using treatment-seeking samples (McEvoy & Mahoney, 2011). Overall, the general IU factor demonstrated the most consistent transdiagnostic predictive utility, with inhibitory IU demonstrating weaker transdiagnostic associations but only in the clinical sample. Although the inhibitory IU group factor demonstrated some unique predictive utility, this finding requires replication due to the low reliability and construct reproducibility index of this group factor. The general IU factor shared the strongest association with worry, which is consistent with previous research that has found a strong association with pathological worry and generalized anxiety disorder, and with the initial conceptualization of IU as a core feature in worry and generalized anxiety disorder (Dugas, Gosselin, & Ladouceur, 2001; Freeston et al., 1994).

The study findings have research and clinical implications. The present results suggest that researchers and clinicians should consider using the total score but not the subscale scores, which is line with recommendations made by other research groups (Hale et al., 2016; Lauriola et al., 2016). The results indicated that the general IU factor is a reliable and well-defined latent variable and that the IUS-12 can be represented as a unidimensional model with little parameter bias. The prospective IU group factor may not be separable or have unique predictive utility in undergraduate and clinical samples. From a theoretical stance, the results may suggest that prospective IU (cognitive appraisals about uncertainty) may not need to be independently interpreted from the general IU factor and rather should be considered a fundamental aspect of general IU. While the inhibitory IU group factor explained only a small proportion of reliable variance in the IUS-12, and therefore need not be considered separate from the general factor, we found that this factor did uniquely and weakly predict social phobia symptoms in undergraduates, and anxiety, social anxiety, and depression in the clinical sample. The greater contribution of inhibitory IU in the clinical sample may be a function of the different measures used across the samples, although it is also possible that inhibitory IU reflects the activation of inhibitory neural pathways at clinical levels of anxiety (Wever et al., 2015). This possibility requires further investigation, and if supported suggests that cognitive-behavioral or exposure-based therapy that aims to build tolerance for uncertainty would benefit from a focus on both the cognitive and behavioral aspects of IU.

The current study is not without limitations, which may inform future research directions. In contrast to the clinical sample who were diagnosed via a structured diagnostic assessment, the undergraduate sample were not subject to diagnostic screening. Thus, we could not rule out that the undergraduate sample did not contain participants with clinical symptom levels. However,

undergraduate samples are commonly used in this research area as they allow for exploration of the dimensional nature of IU through the entire range of symptoms, which is consistent with the NIMH's RDoC initiative (Kozak & Cuthbert, 2016). Nonetheless, it would be valuable to examine the bifactor model in community and other clinical samples to increase confidence in modelling the IUS-12 as a single unidimensional latent variable when investigating structural models. Moreover, the present study used only self-report measures and did not include specific items to assess for carelessness in responding. Finally, the IUS-12 assesses self-reported trait IU rather than real time responses to uncertainty. It is also important to note that the bifactor approach examines the structure of a particular measure, in this case the IUS-12, and not the nature of the underlying the construct and its associated neurobiological or psychobiological effect (Bonifay, Lane, & Reise, 2017). It may be that high inhibitory IU and associated neural circuitry play a more important role (e.g., freezing) during exposure to uncertainty in a salient personal domain, but that a trait self-report measure is unable to comprehensively capture this process distinctly from general IU. Future research that assesses multiple units of analysis (e.g., self-report, behavioral, physiological, neurocircuitry) would be useful for identifying how these processes interact to maintain anxiety and intolerance within the context of uncertainty (Bonifay et al., 2017; Kozac & Cuthbert, 2016).

The current study makes an important incremental contribution to recent literature by replicating the structure of the IUS-12 in an undergraduate sample, but also by extending this approach to a clinical sample within the same study to facilitate comparisons. This study also modelled the predictive utility of the general IU factor and group factors, and provided support for the transdiagnostic nature of general IU (undergraduate and clinical samples) and inhibitory IU (clinical sample only). The multidimensionality of the IUS-12 scores does not appear to be

substantive, and therefore use of the IUS-12 total score (and not subscale scores) is recommended. The IUS-12 total score displayed strong reliability and predictive validity. Researchers and clinicians should also have increased confidence that scores of the IUS-12 can be regarded as a primarily unidimensional representation of general trait IU.

Footnote

[1]All models using the undergraduate sample were re-run without participants who completed the questionnaires faster (*n*=0 due to a positively skewed distribution) or slower (*n*=21) than two standard deviations from the mean, and again without participants who completed the survey faster than an average of three seconds per item (*n*=16). These models were an attempt to guard against undue influence from careless responses. The pattern of findings from these models was identical, and the excluded subgroups did not significantly differ to the remaining group on total IUS-12 scores (*p*s > .05), so only the analyses with the full sample are reported.

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Table 1

Descriptive Statistics, Cronbach's Alpha, and Bivariate Correlations in the Undergraduate and Clinical Samples

	Mean	SD	1	2	3	4	5	6	7	8	9
Undergraduate sample (*N* = 506)											
1. IUS-12	33.25	9.80	.92								
2. GAD-7	7.06	5.38	.62*	.92							
3. SIPS	17.21	13.85	.62*	.62*	.96						
4. PDSS-SR	2.36	2.99	.44*	.63*	.48*	.85					
Clinical sample (*N* = 524)											
5. IUS-12	37.83	10.79					.93				
6. BAI	19.34	19.34					.45*	.93			
7. BDI-II	26.05	26.05					.41*	.58*	.91		
8. PSWQ	61.88	61.88					.56*	.43*	.36*	.91	
9. SIAS	45.42	45.42					.35*	.32*	.32*	.29*	.94

Note. Cronbach's alphas are on the diagonal. SD = standard deviation; IUS-12 = Intolerance of Uncertainty Scale-Short Form; GAD-7 = Generalized Anxiety Disorder-7; SIPS = Social Interaction Phobia Scale; PDSS-SR = Panic Disorder Severity Scale, Self-Report; BAI = Beck Anxiety Inventory; BDI-II = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; SIAS = Social Interaction Anxiety Scale.

* $p < .001$.

Table 2

Goodness-of-Fit Statistics for the Measurement Models

Model	χ^2 (df)	$\Delta\chi^2$ (df)	CFI	TLI	RMSEA	RMSEA 90% CI LL	RMSEA 90% CI UP
Undergraduate sample							
Bifactor	207.72 (42)		.981	.970	.088	.077	.100
Correlated two-factor	349.30 (53)	132.33 (11)[b*]	.966	.958	.105	.095	.116
One-factor	443.25 (54)	61.28 (1)[a*]	.955	.946	.119	.109	.130
Clinical sample							
Bifactor	246.08 (49)		.980	.973	.088	.077	.099
Correlated two-factor	490.96 (53)	155.41 (4)[b]*	.955	.944	.126	.116	.136
One-factor	729.64 (54)	100.34 (1)[a]	.931	.916	.155	.145	.165

Note. CFI = comparative fit index; TLI = Tucker-Lewis fit index; RMSEA = root mean square error of approximation; CI = confidence interval; LL = lower limit; UP = upper limit. Models computed using mean-and variance-adjusted weighted least squares (WLSMV) estimation. $\Delta\chi^2$ computed using Mplus 7.4 DIFFTEST function.

[a] $\Delta\chi^2$ comparing unidimensional and correlated two-factor models in both samples. [b] $\Delta\chi^2$ comparing bifactor and correlated two-factor models in both samples.

* $p < .001$.

Table 3

Standardized Factor Loadings for the Measurement Models of the Intolerance of Uncertainty Scale in an Undergraduate Sample

		One-factor	Two-factor correlated		Bifactor model		
Item			Prospective	Inhibitory	General	Prospective	Inhibitory
1	Unforeseen events upset me greatly	.73	.75		.72	.17	
2	It frustrates me not having all the information I need	.62	.64		.57	.94	
4	One should always look ahead so as to avoid surprises	.69	.71		.70	.07	
5	A small unforeseen event can spoil everything, even with the best of planning	.78	.81		.82	-.03	
8	I always want to know what the future has in store for me	.68	.70		.69	.10	
9	I can't stand being taken by surprise	.78	.80		.81	-.04	
11	I should be able to organize everything in advance	.70	.71		.69	.18	
3	Uncertainty keeps me from living a full life	.79		.82	.79		.15
6	When it's time to act, uncertainty paralyses me	.82		.83	.72		.55
7	When I am uncertain I can't function very well	.82		.84	.74		.44
10	The smallest doubt can stop me from acting	.78		.79	.72		.34
12	I must get away from all uncertain situations	.83		.85	.82		.16
	Coefficient omega				ω = .95	ω_S = .92	ω_S = .92
					ω_H = .90	ω_{HS} = .07	ω_{HS} = .15
	H				.94	.88	.46
	ECV				.80		
	PUC				.53		

Note. N = 506. ω = omega; ω_S = omegaS; ω_H = omegaH; ω_{HS} = omegaHS; H = construct replicability; ECV = explained common variance; PUC = percent uncontaminated correlations. In the two-factor correlated model, the correlation between the factors was .91.

Table 4

Standardized Factor Loadings for the Measurement Models of the Intolerance of Uncertainty Scale in a Clinical Sample

		One-factor	Two-factor correlated		Bifactor	
Item			Prospective	Inhibitory	General	Inhibitory
1	Unforeseen events upset me greatly	.75	.78		.78	
2	It frustrates me not having all the information I need	.71	.73		.73	
4	One should always look ahead so as to avoid surprises	.74	.76		.76	
5	A small unforeseen event can spoil everything, even with the best of planning	.75	.77		.77	
8	I always want to know what the future has in store for me	.74	.76		.76	
9	I can't stand being taken by surprise	.78	.81		.80	
11	I should be able to organize everything in advance	.70	.72		.72	
3	Uncertainty keeps me from living a full life	.75		.78	.72	.25
6	When it's time to act, uncertainty paralyses me	.83		.84	.61	.72
7	When I am uncertain I can't function very well	.87		.89	.70	.56
10	The smallest doubt can stop me from acting	.76		.79	.69	.38
12	I must get away from all uncertain situations	.79		.83	.78	.18
	Coefficient omega				ω = .95	ω_S = .92
					ω_H = .90	ω_{HS} = .24
	H				.94	.64
	ECV				.86	
	PUC				.85	

Note. N = 524. ω = omega; ω_S = omegaS; ω_H = omegaH; ω_{HS} = omegaHS; H = construct replicability; ECV = explained common variance; PUC = percent uncontaminated correlations. In the two-factor correlated model, the correlation between the factors was .85.

Table 5

Summary of Structural Regression Model for the Undergraduate and Clinical Samples

	General Factor				Inhibitory IU Group Factor				Prospective IU Group Factor			
			CI				CI				CI	
	β	SE	LL	UP	*β*	SE	LL	UP	*β*	SE	LL	UP
Undergraduate												
GAD-7	.68*	.03	.62	.74	.08	.06	-.04	.19	.05	.06	-.07	.16
PDSS-SR	.56*	.05	.47	.65	.07	.08	-.08	.23	-.10	.08	-.25	.05
SIPS												
SIA	.57*	.04	.50	.64	.25*	.06	.13	.36	-.01	.06	-.13	.10
FOE	.62*	.03	.56	.69	.23*	.06	.12	.34	-.01	.06	-.13	.10
FAA	.68*	.03	.61	.75	.22*	.06	.10	.34	-.09	.06	-.21	.03
Clinical												
BAI	.45*	.04	.38	.53	.24*	.04	.15	.32				
BDI-II	.42*	.04	.34	.49	.19*	.05	.10	.28				
PSWQ	.63*	.03	.58	.69	.08	.04	-.00	.16				
SIAS	.31*	.04	.23	.39	.33*	.04	.25	.42				

Note. IU = Intolerance of Uncertainty; GAD-7 = Generalized Anxiety Disorder-7; PDSS-SR = Panic Disorder Severity Scale, Self-Report; SIPS = Social Interaction Phobia Scale; SIA = Social Interaction Anxiety Subscale; FOE = Fear of Overt Evaluation Subscale; FAA = Fear of Attracting Attention Subscale; BAI = Beck Anxiety Inventory; BDI-II = Beck Depression Inventory; PSWQ = Penn State Worry Questionnaire; SIAS = Social Interaction Anxiety Scale. CI = 95% confidence interval; LL = lower limit; UP = upper limit.

* $p < .001$.