

The Looming Maladaptive Style Questionnaire: Measurement invariance and relations to anxiety and depression across 10 countries



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ABSTRACT

The Looming Maladaptive Style Questionnaire (LMSQ) is a self-report measure designed to assess the looming cognitive style, a tendency to interpret threats as rapidly approaching and increasing in magnitude. To date, no systematic evaluation on the psychometric properties of the LMSQ across diverse cultural contexts has been done. In the present research, the measurement invariance of the LMSQ test scores was examined in 10 countries ($N = 4000$). Confirmatory factor analysis suggested that a two-factor model (i.e., physical looming and social looming) fitted the data well across countries. Partial measurement invariance was established for the LMSQ scores across the countries whereas full measurement invariance was achieved across gender. Meta-analytic structural equation modeling was applied to examine the unique contributions of the two looming factors to anxiety and depression symptoms. Results indicated that the test scores underlying two looming factors were crucial and valid predictors of symptoms. The LMSQ shows promise as a measure with cross-cultural generalizability and opens new avenues for its use in diverse cultural settings.

1. Introduction

An extensive body of evidence suggests that faulty cognitive appraisals and interpretations of threat may lead individuals to experience greater anxiety symptoms and increase their risk of anxiety disorders (Riskind & Alloy, 2006). Many cognitive models of anxiety postulate that some individuals, more than others, are vulnerable to anxiety because they develop cognitive vulnerabilities comprised of maladaptive negative cognitive styles or beliefs. These cognitive vulnerabilities presumably increase the probability that these individuals develop anxiety symptoms or disorders in response to stressful life events.

According to the looming vulnerability model of anxiety (Riskind, Williams, Gessner, Chrosniak, & Cortina, 2000), when people perceive a potential threat, they want to know whether it is approaching them, and if so, how fast the approach is. When threats are static or dissipating, individuals tend to perceive that it is safer to put off dealing with such threats and their anxiety tapers off. An important feature of this model is that threats are perceived and interpreted as rapidly approaching and increasing in threat values over prior levels such that the proximity, probability, urgency, and other threat values are becoming greater by the moment or over time (Haikal & Hong, 2010; Riskind & Williams, 2005; Riskind et al., 2000). In short, a looming cognitive style (LCS) represents an individual's tendency to

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perceive potentially threatening events as approaching rapidly and escalating in risk levels.

LCS is a distinctive cognitive vulnerability vis-à-vis other anxiety-related vulnerabilities (e.g., anxiety sensitivity or intolerance of uncertainty) by explicitly addressing the importance of perceptions of the approach movement of a threatening stimulus. Other vulnerabilities tend to focus on static trait-like features (e.g., the tendency to be frustrated with unknowns and ambiguity in the case of intolerance of uncertainty) whereas LCS's emphasis is on the dynamic threat perception that changes over time. LCS correlates with anxiety sensitivity and intolerance of uncertainty only moderately and independently predicts anxiety and related syndromes when these and other factors such as negative affectivity are controlled for (Elwood, Riskind, & Olatunji, 2011; Reardon & Williams, 2007; Riskind, Tzur, Williams, Mann, & Shahar, 2007; Sica, Caudek, Chiri, Ghisi, & Marchetti, 2012). In addition, LCS (but not anxiety sensitivity) predicts the intensity of fear reactions after a mood-induction procedure, but not the intensity of sadness reactions (del Palacio-González & Clark, 2015). Intolerance of uncertainty, but not LCS, is positively related to neuroticism – a common factor in anxiety and depression (see Table 8; Hong & Lee, 2015). LCS functions as a danger schema that influences both memory and interpretative biases for threat cues (Riskind et al., 2000; Riskind, Kleiman, Seifritz, & Neuhoff, 2014) and enhance the extent to which people generate stressful life events in an interpersonal context (Riskind, Black, & Shahar, 2010; Riskind et al., 2013).

1.1. Links to anxiety and depression

Previous work has largely established the LCS as a cognitive vulnerability to anxiety. Individuals rated highly on the Looming Maladaptive Style Questionnaire (LMSQ), a self-report measure that assesses the tendency to interpret ambiguous threats as rapidly increasing and approaching, have been shown to be more susceptible to stressful events and anxiety symptoms/disorders. A robust body of evidence has shown that the LCS is more closely related to anxiety than to depression (Reardon & Williams, 2007; Riskind et al., 2000; Riskind, Williams, & Joiner, 2006), and that it predicts future anxiety symptom changes (but not depression) after the occurrence of stressful life events (Adler & Strunk, 2010; Riskind et al., 2000, 2007). LCS predicts increases in anxiety symptoms, worry, and OCD symptoms but not depression symptoms over time (Adler & Strunk, 2010; Elwood et al., 2011; González-Díez, Calvete, Riskind, & Orue, 2015; Riskind et al., 2007; Sica et al., 2012). LCS is also found to be elevated among individuals with generalized anxiety disorder compared to individuals with depression or healthy controls (Riskind & Williams, 2005).

Despite the strong specificity to anxiety shown by the LCS, emerging data suggest that its associations with depression might be substantial as well, under certain conditions. The LCS of patients with terminal leukaemia predicted both anxiety and depression (Levin, Li, & Riskind, 2007), presumably because the inevitable negative outcomes (suffering and early death) could not be evaded. Several other studies demonstrate that LCS predict elevated symptoms of both anxiety and depression (Kleiman & Riskind, 2012; Riskind et al., 2013; Tzur-Bitan, Meiran, Steinberg, & Shahar, 2012), suggesting that it may reflect a central mechanism in anxiety and depression comorbidity. Given these findings, more attention is needed to examine whether LCS predicts depression as well as anxiety. The conditions under which LCS might predict depression may have to do with the timing of the threat and the perceived potential of evading harm. When threat is uncertain – and there is still a possibility of evading harm – anxiety might be the strongest reaction. However, when one perceives that harm cannot likely be evaded, or already happened, depression should also likely occur.

1.2. Psychometric properties of the LMSQ

The LMSQ is divided into two subscales: social looming – which pertains to an anticipatory style for socially threatening scenarios, and physical looming – which refers to a style for scenarios that are physically dangerous (Riskind et al., 2000). Although these two subscales are typically highly correlated, and often function as a unitary construct, recent findings have indicated that they are predictive of different outcomes. For example, a study by Riskind et al. (2014) on the auditory looming effect found that among anxious participants, the physical looming subscale predicted a tendency to overestimate the closeness of an approaching sound source, whereas the social looming subscale predicted the opposite tendency to underestimate the closeness of the sound source. Another recent study showed that participants who were shown images of potentially ambiguous approaching threats (e.g., different animals) showed stronger immobilizing freeze responses if they had the physical (but not the social) component of LCS (Riskind, Sagliano, Trojano, & Conson, 2016). Furthermore, the social looming subscale has been found to predict social anxiety better than the physical looming subscale (Brown & Stopa, 2008; González-Díez, Orue, Calvete, & Riskind, 2014; Riskind, Rector, & Cassin, 2011). Hence, there is a need to examine the effects of each subscale separately as well as the effects of the total LMSQ scale in research.

Numerous studies have found strong internal consistency reliabilities for the total LMSQ and its subscale scores (e.g., Adler & Strunk, 2010; Brown & Stopa, 2008; Reardon & Williams, 2007; Riskind et al., 2000). González-Díez et al. (2014) examined the structure and measurement invariance across subsamples, and the concurrent validity, consistency, and stability of a Spanish translation of the LMSQ ($N = 1128$, 56.47% women). In their model, they specified LMSQ items loading onto scenarios (i.e., first-order factors), and scenarios loading onto the social and physical looming factors (i.e., second-order factors). (The Measures section includes information on the LMSQ scenarios.) This hierarchical two-factor model yielded a better fit than a single-factor (i.e., overall looming) model. Moreover, they conducted a multiple-group analysis that indicated metric invariance of the model for men and women and for groups that displayed clinically significant social anxiety and those that did not. González-Díez et al. reported that women scored higher on the LMSQ than men. However, these means were based on observed scores rather than latent factor means.

1.3. The present study

The looming vulnerability model of anxiety and threat appraisal posits that the perception of rapidly rising risk and approaching danger is an evolutionarily-based parameter of threat cognition and therefore should apply species-wide to all humans (Riskind et al., 2000). Indeed, defensive reactions to approaching danger are also observed in all other animals, including invertebrate animals (Riskind, 1997; Riskind et al., 2014). Thus the looming vulnerability model presupposes that the association between LMSQ and relevant criteria (i.e., anxiety and depression) should be present across distinct cultural groups. There is a critical need to examine the validity of the LMSQ scores in predicting symptoms in a cross-cultural context. However, such a systematic test has yet to be done.

Information about the measurement properties of the LMSQ as used in various cultural contexts is scarce, casting doubt on whether the LMSQ can be used reliably across cultures. This is especially important because the questionnaire is based on people's perceived reactions to scenarios or vignettes (e.g., threat of a potential social rejection). The scenarios of the LMSQ may elicit cultural-specific influences on responses. Therefore, our first research goal was to address the question of whether the measurement properties of LMSQ remain invariant across cultural groups. This would allow researchers to ascertain if the LMSQ is being interpreted and responded in the same manner across

Table 1
Descriptive Statistics across the 10 Countries.

Country	N	Sample	Mean age	Per. female	Physical Looming		Social Looming		Total Looming	
					M (SD)	α	M (SD)	α	M (SD)	α
Canada	183	Student	20.1	68.3	3.28 (0.79)	0.84	3.25 (0.71)	0.80	3.27 (0.66)	0.87
Croatia	436	Community	27.9	83.7	2.73 (0.88)	0.85	2.65 (0.80)	0.82	2.69 (0.74)	0.88
Italy	691	Community	52.8	54.7	3.14 (0.82)	0.87	3.12 (0.86)	0.89	3.13 (0.75)	0.91
Japan	258	Student	18.5	63.8	3.45 (0.68)	0.79	3.58 (0.65)	0.77	3.57 (0.58)	0.83
Nepal ^a	293	Student	23.8	–	2.68 (0.81)	0.84	2.70 (0.76)	0.79	2.66 (0.74)	0.88
Serbia	298	Student	28.3	77.5	3.09 (0.78)	0.88	2.87 (0.74)	0.84	2.98 (0.68)	0.90
Singapore	331	Student	20.4	75.8	3.24 (0.73)	0.84	3.27 (0.80)	0.86	3.25 (0.68)	0.89
Spain	743	Student	19.0	52.0	3.17 (0.77)	0.88	3.07 (0.76)	0.87	3.12 (0.69)	0.91
Turkey	563	Student	20.7	67.6	3.31 (0.85)	0.86	3.31 (0.82)	0.84	3.31 (0.73)	0.89
US ^b	204	Student	19.4	74.0	3.53 (0.84)	0.89	3.19 (0.90)	0.88	3.36 (0.78)	0.92

Note. Per. female = Percentage of female participants in sample.

^a Gender information is unavailable.

^b Age information is available for 73 participants only.

different cultural (or gender) groups. This would entail examining if structural properties like the factor structure and loadings are equivalent across groups. Establishing invariance of the LMSQ would allow more confidence when interpreting associations between LMSQ scores and other variables across cultures (see Vandenberg & Lance, 2000). A more stringent form of invariance where indicator intercepts are constrained to be equal across cultures would allow for more confidence in comparing mean differences between groups.

Upon confirming the measurement invariance of the LMSQ, our second research goal was to take advantage of a meta-analytic structural equation modeling approach to examine the validity of the LMSQ subscales in relation to depression and anxiety symptoms from a cross-cultural perspective. If it can be assumed that the LMSQ represents a species-wide cognitive risk mechanism, the averaged association between the LMSQ and symptoms should be meaningful and nontrivial. Specifically, we sought to determine whether the two subtypes of LMSQ – looming to physical threat and looming to social threat – are both valid and equivalent predictors of symptoms. As previously reviewed, the social and physical LMSQ subtypes have been found to predict different outcomes. No previous studies, however, have systematically explored whether LMSQ subtypes differ in the extent to which they predict anxiety and depression. Under most conditions, for example, the social looming subtype might be more strongly related to both symptoms. This is because most people might generally have more experience with social (e.g., pending social rejection) than with physical threats (e.g., possible traffic accident). In addition, we expected to replicate LMSQ's robust association with anxiety, while recognizing that its link to depression could be substantial as well.

2. Method

2.1. Participants and procedure

Data were available from a total of 4000 participants from ten countries (see Table 1), after omitting 25 cases (0.6%) that had missing responses on more than half of the LSMQ. Missing item entries (at most 0.02%), which were consistent with missing completely at random (Little's MCAR test, $\chi^2(169) = 198.86, p = 0.06$), were then imputed using the expectation-maximization procedure (Graham, 2009). All participants were university students, with the exceptions of the samples from Croatia and Italy, which consisted of community volunteers. Participants in Canada, Singapore, and the United States completed the self-report measures in English whereas participants in the other countries completed the measures in their native languages. Back translation procedures were done for the measures in all countries

except for Croatia, Nepal, and Japan.¹

Some of these data sets have been reported in previous studies (Calvete, Orue, Riskind, & González-Díez, 2016; del Palacio-González & Clark, 2015; Hong, 2013; Khatri, Reynolds, & Riskind, 2003), although none of them were addressing the issue of measurement invariance from a cross-cultural perspective.

¹ Details of participant recruitment and translation of measures (if applicable) are as follows. The year of data collection is reported after the country name. (a) **Canada** (2009): Undergraduate students were recruited through the psychology department participant pool and they participated for course credit. The study involved examining emotional reactions to movie clips but the LMSQ and other questionnaires were administered before the film mood-induction. (b) **Croatia** (2014): Call for participation was published on several websites intended for gathering research data and publishing news on social sciences for the general public. Participation in the survey, administered online, was anonymous and voluntary, without compensation. No back-translation procedure was done for the LSMQ in this sample. (c) **Italy** (2012): Participants were parents of undergraduate students. Each student was given two sealed envelopes to bring home; both parents received one set of questionnaires each. Participation was voluntary with no payment offered. Three researchers independently translated the LMSQ from English to Italian and then reached agreement on a common version. This version was then back-translated by a bilingual individual with an extensive knowledge of psychological research. The back-translation was refined by J. Riskind (i.e., the author of LMSQ). This refined version went through another round of back-translation by another bilingual expert before settling on the final version. The Italian version of the LMSQ had shown good psychometric properties (Sica et al., 2012). (d) **Japan** (2011): Students attending introductory psychology courses were asked to complete questionnaires during classes. Participation was voluntary with no compensation. The LMSQ was translated into Japanese by Y. Sugiura but no back-translation was done. (e) **Nepal** (2007): Participants were volunteers recruited via convenience sampling. No back-translation procedure was done for the LSMQ in this sample. (f) **Serbia** (2013): Undergraduate students participated in the study in exchange for course credit. The LMSQ was back-translated by two bilingual individuals (one of them L. Mihic). Both were Serbs who had lived in an English-speaking country for more than 10 years. Little discrepancy was found between the original and back-translated versions of the LMSQ. (g) **Singapore** (2009): Undergraduate students were recruited through the psychology department participant pool and they participated for course credit or cash token. The sample was from two related studies that involved students completing self-report measures on personality, cognitive risk factors, and symptoms. (h) **Spain** (2011): Participants were students from a university and three vocational schools. Participants filled in the questionnaires in their classrooms. The responses were anonymous and the participation was voluntary with no compensation. The LMSQ were translated into Spanish using a full back-translation method and it showed good psychometric properties (González-Díez et al., 2014). (i) **Turkey** (2010): Participants were university students from various universities in Istanbul who were enrolled in psychology classes. They were asked to complete questionnaires in class and received course credit in return for participation. The LMSQ was translated into Turkish by two psychologist that were fluent in both languages. Back-translation was done and compared to the original English version. Disagreements on certain items were resolved by a panel of 15 bilinguals. (j) **United States** (2008): Undergraduate students were recruited through the psychology department participant pool and they participated for course credit.

2.2. Measures

The Looming Maladaptive Style Questionnaire (LMSQ; [Riskind et al., 2000](#)) consists of six scenarios that depict impending threatening situations. Three scenarios describe threats possibly leading to physical harm (i.e., car engine problem, heart palpitations, and traffic accident) and the remaining scenarios describe threats associated with social situations (e.g., relationship break-up, social rejection, and poor public speaking). Participants were instructed to imagine themselves being in those scenarios and respond to four questions per scenario using a 5-point Likert-type scale ranging from 1 (*not at all*) to 5 (*very much*). The questions were: (a) “How worried or anxious does your imagining this scene make you feel?” (b) “In this scene, are the chances of the threat decreasing, or increasing and expanding with each moment?” (c) “Is your level of threat in the scenario staying fairly constant, or is it growing rapidly larger with each passing moment?” and (d) “How much do you visualize the threat as in the act of becoming progressively worse?” For each scenario, the second to fourth questions were averaged to derive a scenario-level looming score. These scenario-level scores could then be used to obtain the total looming score or scores associated with physical and social threats, respectively.

Data on anxiety and depression were available from all countries, except for three countries (Nepal, Serbia, and the US) that did not have a depression measure. For general anxiety, the following instruments were used: (a) Beck Anxiety Inventory ([Beck, Epstein, Brown, & Steer, 1988](#); in Italy, Nepal, Singapore, and Turkey), (b) Depression Anxiety Stress Scales – Anxiety ([Lovibond & Lovibond, 1995](#); in Croatia), (c) Mood and Anxiety Symptom Questionnaire – Nonspecific Anxiety ([Watson & Clark, 1991](#); in Canada), (d) Symptom Checklist-90-Revised – Anxiety ([Derogatis & Unger, 2010](#); in Spain), (e) State-Trait Anxiety Inventory – Trait Anxiety ([Spielberger, 1989](#); in Japan and the US), and (f) a locally developed measure of anxiety ([Tovilović & Novović, 2009](#); in Serbia). For depression, the following measures were used: (a) Beck Depression Inventory-II ([Beck, Steer, & Brown, 1996](#); used in Italy, Singapore, and Turkey), (b) Center for Epidemiologic Studies v Depression Scale ([Radloff, 1977](#); in Japan), (c) Depression Anxiety Stress Scales – Depression ([Lovibond & Lovibond, 1995](#); in Croatia), (d) Mood and Anxiety Symptom Questionnaire – Nonspecific Depression ([Watson & Clark, 1991](#); in Canada), and (e) Symptom Checklist-90-Revised – Depression ([Derogatis & Unger, 2010](#); in Spain). Reliabilities of these symptoms measures were all excellent with coefficient alpha's greater than 0.84, with the exception of the Mood and Anxiety Symptom Questionnaire – Nonspecific Anxiety subscale used in the Canadian sample ($\alpha = 0.69$).

2.3. Data analysis

Following [González-Díez et al. \(2014\)](#), we examined a hierarchical structure of the LMSQ where first-order latent factors (i.e., LMSQ scenarios) were derived from their respective observed indicators (i.e., the second to fourth items within each scenario). The six latent scenario factors were specified to load onto (a) a single second-order factor representing an overall looming cognitive style, or (b) two second-order latent factors reflecting the looming to physical and social threats. [Fig. 1](#) depicts the structural model with two second-order latent factors. Model comparisons using confirmatory factor analysis (CFA) were done to determine the model that best fitted the data.²

Measurement invariance was evaluated using AMOS version 23 following the general procedure outlined by [Milfont and Fischer \(2010\)](#) and [Vandenberg and Lance \(2000\)](#). After establishing the most plau-

² A bifactor model was also considered. Due to the hierarchical structure of the LMSQ (see [Fig. 1](#)), the bifactor model has to specify two group factors (i.e., physical and social looming) and the general looming factor with loadings onto the scenarios. However, such a bifactor model is not identified as bifactor models need to have loadings directly onto the observed indicators (i.e., items).

sible LMSQ structure across the countries, multiple-group CFAs were conducted across countries and gender. The least restrictive model (i.e., configural invariance) was tested followed by a series of subsequent analyses that imposed increasing model constraints (e.g., whether factor loadings, intercepts, and error variances were invariant). Model fit was evaluated using the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root-mean-square error of approximation (RMSEA) and its 90% confidence interval, and the Browne-Cudeck Criterion (BCC). In comparing models, the use of the chi-square difference test has been criticized as being excessively stringent in testing invariance due to its sensitivity to sample size. Therefore, we adopted the recommendation that a change of 0.01 or less in CFI, supplemented with a change of 0.015 or less in RMSEA, would indicate invariance of the more constrained model (see [Chen 2007](#); [Cheung & Rensvold, 2002](#)). In the event of discrepancy between the two criteria, Δ CFI is the main criterion to be used because Δ RMSEA is more affected by model complexity and sample size ([Chen, 2007](#)). For completeness's sake, we also presented the chi-square difference tests in our results.

Meta-analyses were conducted to estimate the mean correlation coefficients among the LMSQ factors, depression, and anxiety ([Lipsey & Wilson, 2001](#)). Pearson's r coefficients coded from the studies were Z-transformed before being weighted by the inverse variance. Mean effect sizes were then converted back to r coefficients using the Z-to- r transformation for clarity of presentation. These analyses provided the averaged bivariate correlations between the variables summarized across the studies conducted in different countries. The Comprehensive Meta-Analysis version 2 program ([Borenstein, Hedges, Higgins, & Rothstein, 2005](#)) was used for these analyses.

[Cheung and Chan's \(2005, 2009\)](#) two-stage structural equation modeling (TSSEM) approach, a form of meta-analytic structural equation modeling, was used to explicate the unique paths between the LMSQ higher-order factors and depression/anxiety symptoms. This approach is superior to the traditional univariate methods in that it (a) utilizes the total sample size (rather than taking the arithmetic or harmonic mean) for all studies, (b) handles missing data appropriately, and (c) integrates meta-analysis and structural equation modeling procedures within a unified framework. In the first stage of TSSEM, correlation matrices obtained from the various studies were combined into a pooled matrix using a random effects model ([Cheung, 2014](#)). In the second stage, a path model was specified using a weighted least squares estimation procedure ([Browne, 1984](#)) with inputs being the pooled correlation matrix (obtained in stage 1) and the asymptotic sampling covariance matrix. These analyses were conducted using the R “metaSEM” package developed by [Cheung \(2015a\)](#). Interested readers may refer to [Cheung \(2015b\)](#) for technical details or to [Hong and Cheung \(2015\)](#) for a practical application of the TSSEM.

3. Results

Preliminary analyses were conducted to determine the distributional properties of the LMSQ items. Across countries, the individual items did not deviate drastically from normality (i.e., skewness was between -1.02 to 1.63 and kurtosis was between -1.21 and 1.65). However, multivariate kurtosis ([Mardia, 1970](#)) was significant, suggesting the possibility of non-normal data. We employed the bootstrapping procedure in AMOS, using 250 bootstrap replications, to derive model parameters for comparison with the corresponding parameters obtained from maximum likelihood (ML) estimation. Parameters and their standard errors obtained were almost identical between the two procedures, indicating that the multivariate non-normality did not severely impact the current results. In addition, although our data were ordinal, we were confident that parameter estimation by ML would be precise, especially when the item response format was based on 5 categories and item distributions were fairly normal (see [Babakus, Ferguson, & Jöreskog, 1987](#); [Green, Akey, Fleming, Hershberger, & Marquis, 1997](#); [Rhemtulla, Brosseau-](#)

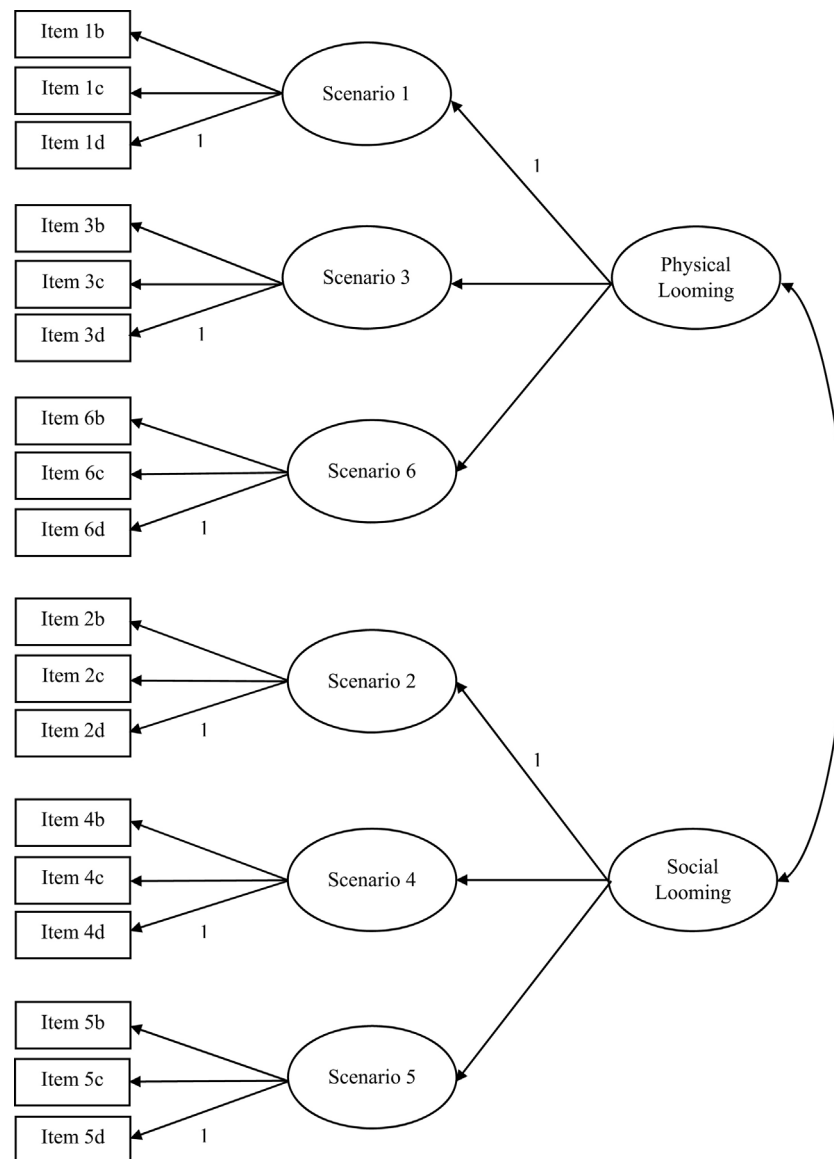


Fig. 1. Confirmatory factor analysis of the LMSQ. This model shows two second-order latent factors of physical and social looming.

Liard, & Savalei, 2012).

A critical reason for using ML estimation here is to facilitate the evaluation of models within a multiple-group measurement invariance framework. Model comparisons have been done primarily through assessing the magnitude of change in approximate fit indices such as ΔCFI and $\Delta RMSEA$ (Chen, 2007; Cheung & Rensvold, 2002). However, these criteria were developed under the assumption of normal-continuous data distribution and were estimated through ML. Little research has been done to examine if the approximate fit index change criteria are appropriate to evaluate invariance in the context of other estimators like the weighted least squares with mean and variance adjusted statistics (WLSMV) – the preferred estimator for categorical non-normal data. Sass, Schmitt, and Marsh (2014) examined the performance of several estimators as used in evaluating measurement invariance and they cautioned that the change in approximate fit index criterion should not be used with WLSMV estimation. In the absence of a reliable criterion that can be used with WLSMV, we decided to use ML as our primary estimation procedure. As we discussed later on, we also used WLSMV to examine if our CFA results would differ from those obtained via ML.

Single-group CFAs were first conducted separately for each country to evaluate the validity of one- versus two-factor models underlying the

LMSQ. Because the LMSQ versions used in Japan and Nepal had the first scenario modified, they were excluded for the purposes of the single-group CFA analyses.³ In each single country CFA, an indicator loading was fixed as 1 to scale the latent factors, and error covariances were fixed to 0 (see Fig. 1). The one-factor model yielded a good fit to the data. Across the eight countries, the CFI ranged between 0.932 and 0.974; TLI between 0.910 and 0.965, and RMSEA between 0.049 and 0.085. For the two-factor model, the CFI ranged between 0.934 and 0.975; TLI between 0.912 and 0.966, and RMSEA between 0.048 and 0.084. The fit indices showed that the models fitted data the best for Spain but the worst for Italy. Chi-square difference tests indicated that the one-factor model should be preferred for Canada, Croatia, and Serbia. The two-factor solution was preferred for the rest of the countries, with the estimated correlation between the factors ranging from 0.84 to 0.91. It appeared that the very strong correlation between the physical and social looming factors could render them indistinguishable in some countries.

³ The first scenario was modified to depict the looming threat of flying in an airplane in the Japanese sample and of encountering pick-pockets for the Nepalese sample. Modifications were done by the local researchers to better suit their respective cultural contexts.

Table 2
Tests of Measurement Invariance for the 2-Factor Hierarchical Model across Eight Countries.

Models	χ^2 (df)	CFI	TLI	RMSEA [90% CI]	BCC	Model Comparisons
1. Configural	2892.67 (1024) ^a	0.955	0.946	0.023 [0.022; 0.024]	3928.49	
2. Metric (loadings equal) ^b	3178.71 (1136) ^a	0.951	0.947	0.023 [0.022; 0.024]	3976.80	1 vs. 2: Δ CFI = -0.004; Δ RMSEA = 0.000; $\Delta\chi^2 = 286.04^*$
3. Scalar (intercepts equal)	4309.16 (1248) ^a	0.926	0.927	0.027 [0.026; 0.028]	4868.52	2 vs. 3: Δ CFI = -0.025; Δ RMSEA = 0.004; $\Delta\chi^2 = 1130.45^*$
3a. Partial scalar	3544.23 (1185) ^a	0.943	0.941	0.024 [0.023; 0.025]	4238.31	2 vs. 3a: Δ CFI = -0.008; Δ RMSEA = 0.001; $\Delta\chi^2 = 365.52^*$
4. Error variances equal, partial scalar ^b	4762.18 (1353) ^a	0.918	0.925	0.027 [0.026; 0.028]	5099.67	3a vs. 4: Δ CFI = -0.025; Δ RMSEA = 0.003; $\Delta\chi^2 = 1217.95^*$
4a. Error variances equal (scenarios only), partial scalar	3828.19 (1227) ^a	0.937	0.937	0.025 [0.024; 0.026]	4433.12	3a vs. 4a: Δ CFI = -0.006; Δ RMSEA = 0.001; $\Delta\chi^2 = 283.96^*$
5. Factor variances equal	3873.41 (1241) ^a	0.936	0.936	0.025 [0.024; 0.026]	4448.63	4a vs. 5: Δ CFI = -0.001; Δ RMSEA = 0.000; $\Delta\chi^2 = 45.22^*$
6. Factor covariances equal	3898.46 (1248) ^a	0.936	0.937	0.025 [0.024; 0.026]	4458.82	5 vs. 6: Δ CFI = -0.000; Δ RMSEA = 0.000; $\Delta\chi^2 = 25.05^*$
7. Factor means equal	4061.75 (1262) ^a	0.932	0.934	0.025 [0.024; 0.026]	4592.39	6 vs. 7: Δ CFI = -0.004; Δ RMSEA = 0.000; $\Delta\chi^2 = 163.29^*$

Note. CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation; CI = Confidence interval; BCC = Browne-Cudeck Criterion; Δ CFI = CFI_{unconstrained} - CFI_{constrained}; Δ RMSEA = RMSEA_{constrained} - RMSEA_{unconstrained}. For model comparisons, a Δ CFI value smaller than or equal to -0.010, supplemented by a Δ RMSEA value smaller than or equal to 0.015, implies invariance of the constrained model (see Chen, 2007; Cheung & Rensvold, 2002).

^a First- and second-order factor loadings were simultaneously constrained.

^b Error variances of indicators and scenarios were simultaneously constrained.

* $p < 0.05$.

Using multiple-group analysis, we compared the configural models (i.e., one- versus two-factor) across the eight countries to determine which model fitted the cross-cultural data better. The one-factor model yielded a good fit to the data, $\chi^2(1032, N = 3449) = 2949.85, p < 0.001, CFI = 0.954, TLI = 0.945, RMSEA = 0.023$ (90%CI = 0.022–0.024), AIC = 3909.44, BCC = 3968.68. The two-factor model also obtained a good fit, $\chi^2(1024, N = 3449) = 2892.67, p < 0.001, CFI = 0.955, TLI = 0.946, RMSEA = 0.023$ (90%CI = 0.022–0.024), AIC = 3868.74, BCC = 3928.49. Chi-square difference test suggested that the two-factor model should be preferred over the one-factor model, $\Delta\chi^2(8) = 57.18, p < 0.001$, as with the AIC and BCC (i.e., lower for two-factor model). The preceding analyses were repeated using the WLSMV estimation in Mplus (Muthén & Muthén, 1998–2012), yielding very similar conclusions. The two-factor model was hence adopted as the basis for further evaluation of measurement invariance. Descriptive statistics and internal consistency reliabilities of the looming factors are presented in Table 1.

Next, we examined the measurement invariance of the two-factor LSMQ model across eight countries. Data from Japan and Nepal were excluded because of their versions had the first scenario modified. Table 2 presents the hierarchy of models with increasing constrains imposed on model parameters. Model 1 (configural) tested the invariance of a two-factor LSMQ model and data fit was good. Model 2 (metric) was then considered where the first- and second-order factor loadings were simultaneously constrained to be equal across countries. This model was invariant using the Δ CFI and Δ RMSEA criteria (Chen, 2007; Cheung & Rensvold, 2002). However, invariance for Model 3 (scalar) was not supported and close inspection of the parameter estimates suggested that items associated with three LMSQ scenarios (i.e., relationship breakup, negative audience reaction, and traffic accident) were likely invariant across countries. Intercepts of items associated with the three scenarios were specified to be equal across countries whereas the remaining intercepts were freely estimated. This resulted in a partial scalar invariance model (Model 3a) and it was preferred over the metric invariance model. Model 4 (equal error variances of both indicators and scenarios; and partial scalar invariance) yielded a relatively poor fit and Model 4a (a modification where only the error variances of the scenarios were constrained to be equal) was preferred over Model 3a.

Models 5 and 6 implied that it was reasonable to conclude that the variances and covariances of the looming factors were invariant. Given that partial scalar invariance allowed for meaningful comparison of factor means (Byrne, Shavelson, & Muthén, 1989; Steenkamp & Baumgartner, 1998), the equality of factor means was evaluated (Model 7). The change in CFI criterion indicated that the equal means model should be preferred. Nonetheless, we explored possible cross-country differences while cognizant of the possibility that these differences might be small. Using the US sample as the reference group, it appeared that the physical looming factor mean was lower for Croatia (difference = -0.44, SE = 0.09) and Italy (difference = -0.21, SE = 0.08), all $ps < 0.01$. For the social looming factor, the means for Croatia (difference = -0.36, SE = 0.07), Italy (difference = -0.17, SE = 0.06), and Spain (difference = -0.19, SE = 0.06) were lower than the US, all $ps < 0.01$. The other countries did not differ in factor means from the US. Based on Model 7, standardized second-order factor loadings were 0.60, 0.68, and 0.71 for physical looming and 0.60, 0.65, and 0.70 for social looming. The correlation between the two factors was 0.89. Overall, these analyses provide support for partial measurement invariance for the LSMQ factors across the countries.

Table 3 presents the test of measurement invariance of the two-factor model across gender. Data from Japan and Nepal were included because country-level differences were not the main focus here and the missing data associated with the modified scenarios for these two countries could be easily accommodated by maximum likelihood estimation. Invariance was achieved for Models 1 through 4, though

Table 3
Tests of Measurement Invariance for the 2-Factor Hierarchical Model across Gender.

Models	χ^2 (df)	CFI	TLI	RMSEA [90% CI]	BCC	Model Comparisons
1. Configural	2045.21 (256) ^a	0.958	0.944	0.044 [0.042; 0.045]	2292.05	
2. Metric (loadings equal) ^b	2065.20 (272) ^a	0.958	0.947	0.042 [0.041; 0.044]	2279.66	1 vs. 2: Δ CFI = -0.000; Δ RMSEA = -0.002; $\Delta\chi^2 = 19.99$, ns.
3. Scalar (intercepts equal)	2178.53 (288) ^a	0.956	0.948	0.042 [0.041; 0.044]	2360.63	2 vs. 3: Δ CFI = -0.002; Δ RMSEA = 0.000; $\Delta\chi^2 = 113.33$
4. Error variances equal ^b	2294.66 (312) ^a	0.954	0.949	0.041 [0.040; 0.043]	2428.20	3 vs. 4: Δ CFI = -0.002; Δ RMSEA = -0.001; $\Delta\chi^2 = 116.13$ ^c
4a. Error variances equal (scenarios only)	2188.90 (294) ^a	0.956	0.949	0.042 [0.040; 0.043]	2358.85	3 vs. 4a: Δ CFI = -0.000; Δ RMSEA = 0.000; $\Delta\chi^2 = 10.37$, ns.
5. Factor variances equal	2191.69 (296) ^a	0.956	0.949	0.042 [0.040; 0.043]	2357.60	4a vs. 5: Δ CFI = -0.000; Δ RMSEA = 0.000; $\Delta\chi^2 = 2.79$, ns.
6. Factor covariances equal	2193.02 (297) ^a	0.956	0.949	0.042 [0.040; 0.043]	2356.91	5 vs. 6: Δ CFI = -0.000; Δ RMSEA = 0.000; $\Delta\chi^2 = 1.33$, ns.
7. Factor means equal	2264.76 (299) ^a	0.954	0.948	0.042 [0.041; 0.044]	2424.60	6 vs. 7: Δ CFI = -0.002; Δ RMSEA = 0.000; $\Delta\chi^2 = 71.74$ ^c .

Note. There were 1263 males, 2431 females, and 306 unreported. CFI = Comparative fit index; TLI = Tucker-Lewis index; RMSEA = Root mean square error of approximation; CI = Confidence interval; BCC = Browne-Cudeck Criterion; Δ CFI = CFI_{constrained} - CFI_{unconstrained}; Δ RMSEA = RMSEA_{constrained} - RMSEA_{unconstrained}. For model comparisons, a Δ CFI value smaller than or equal to -0.010, supplemented by a Δ RMSEA value smaller than or equal to 0.015, implies invariance of the constrained model (see [Chen, 2007](#); [Cheung & Rensvold, 2002](#)).

^a First- and second-order factor loadings were simultaneously constrained.

^b Error variances of indicators and scenarios were simultaneously constrained.

* $p < 0.05$.

constraining only the scenario-level error variances but freeing the item-level error variances (i.e., Model 4a) could represent a compromise. Tests of population heterogeneity suggested that factor variances, covariances, and latent means were invariant across gender. Although the female mean was higher than the male mean by 0.23 ($p < 0.001$) for physical looming and by 0.18 ($p < 0.001$) for social looming, these differences probably have trivial practical or clinical significance. The estimated standardized second-order factor loadings were strong (0.61–0.71) and the correlation between the two latent factors was 0.91.⁴

Achieving metric invariance for the LMSQ implies similar LMSQ factor structures across countries and it is appropriate to synthesize the associations between LMSQ factors and other variables of interests across countries via meta-analysis. Although different depression and anxiety measures were used across samples, meta-analysis allowed us to collate and average the correlation coefficients among the measures. For example, all correlations between physical looming and depression symptoms (measured by different scales) were extracted from the samples. Because correlations are standardized coefficients that can be directly compared across samples, they can be combined meta-analytically. [Table 4](#) presents the estimated effect sizes of the associations among the LMSQ subscales and symptoms derived from univariate meta-analysis. All mean correlations were significant; that is, confidence intervals did not include zero. The associations between social looming and symptoms were stronger than those between physical looming and symptoms. Heterogeneity of effect sizes, as indicated by a significant Q statistic and an I^2 greater than 75%, was observed for the association between depression and anxiety. Instead of conducting formal moderation analysis, we visually inspected the effect sizes for this association in view of the small number of studies included. Effect sizes ranged between 0.32 (Turkey) and 0.72 (Croatia); the latter's strong correlation could be attributed to the specific measure used (i.e., DASS).

More important to our current purposes, we conducted TSSEM to determine the unique contributions of physical versus social looming factors on depression and anxiety symptoms. The first stage of the TSSEM suggested that the assumption of homogeneity of the correlation matrices was not tenable, $\chi^2(45) = 165.69$, $p < 0.001$. Also, the I^2 of the individual correlations ranged from 0% to 88% (mean = 38%), indicating that a random effects model would be more appropriate for the current data than a fixed effects model when combining correlation matrices across studies ([Cheung, 2014](#)). The mean correlation coeffi-

⁴ The measurement invariance analyses across countries and gender were reanalysed without the two community samples (i.e., Croatia and Italy) to determine if the findings would differ. Omitting the community samples did not alter the conclusions regarding measurement invariance.

Table 4
Meta-Analyses of Looming and Symptom Variables.

Association	k	N	r	95% CI	Q	I^2
Physical Loom – Social Loom	10	3992	0.57	0.53–0.60	22.31 [*]	59.65
Physical Loom – Depression	7	2949	0.22	0.16–0.27	13.44	55.35
Physical Loom – Anxiety	10	2754	0.26	0.21–0.31	18.15	50.40
Social Loom – Depression	7	2949	0.29	0.24–0.34	14.12	57.52
Social Loom – Anxiety	10	2753	0.28	0.21–0.35	32.98 [*]	72.71
Depression – Anxiety	7	2092	0.59	0.49–0.67	60.03 [*]	90.01

Note. k = number of studies; N = aggregate sample size; r = mean weighted effect size; CI = confidence interval; Q = heterogeneity statistic; I^2 = true heterogeneity percentage; Physical Loom = Physical looming factor; Social Loom = Social looming factor.

* $p < 0.01$.

cients (not presented here but available upon request) obtained via this multivariate pooling procedure is very similar to those presented in [Table 4](#). This multivariate approach is considered superior to the univariate approach because dependence among correlation coefficients is accounted for ([Becker, 2000](#)).

The pooled correlation matrix was then used as input data for a path analysis where symptoms were regressed on the two LMSQ factors (see [Fig. 2](#)). As the model was just-identified, all fit indices were perfect. Nonetheless, it was informative to obtain the unique path estimates between the LMSQ factors and symptoms, while controlling for the overlap between (a) the LMSQ factors and (b) the residuals of depression and anxiety symptoms. All parameters were significant with 95% confidence intervals non-inclusive of zero. Both looming factors uniquely predicted depression and anxiety symptoms, accounting for 10% of the variance in each of the symptoms. The predictability of social looming on depression was appreciably larger than that of physical looming. Conversely, the magnitude of path coefficients were similar across the looming factors in their prediction of anxiety.

4. Discussion

The hierarchical factorial structure of the LMSQ was examined across eight countries and a two-factor structure appeared to fit the cross-cultural data better than a one-factor model. To be sure, in some countries (Canada, Croatia, and Serbia), the two LMSQ factors were indistinguishable such that a one-factor model would parsimoniously accommodate the data. Given that the population correlation between the two LMSQ factors was expected to be strong, sampling error might result in strong correlation coefficients in some cases that tipped the balance toward a one-factor model. Nonetheless, across the eight countries, a two-factor solution (i.e., physical and social looming) was deemed more appropriate, consistent with previous research ([González-Díez et al., 2014](#)). Also, in view of the LMSQ subtypes' differential

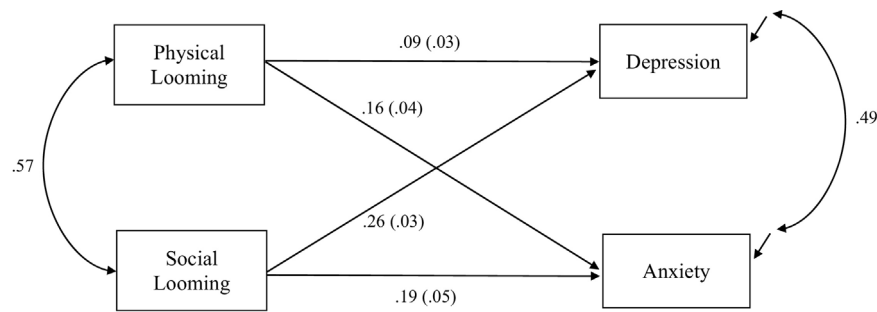


Fig. 2. Hypothesized path model. Standardized parameter estimates with standard errors (in parentheses) are shown. All parameters were significant.

validity with other constructs (e.g., Brown & Stopa, 2008; Riskind et al., 2011, 2014, 2016), we decided to adopt the two-factor model in the current analysis.

Configural and metric invariances were established for the two-factor LMSQ model across the eight countries. The distinction between items pertaining to looming of physical threat versus social threat was meaningful to respondents across cultures. Furthermore, items and scenarios displayed similar factor loadings across cultures, suggesting that they were interpreted in the same way regardless of cultural affiliation. Scalar invariance was partially achieved; however, this finding was not entirely unexpected. Achieving full measurement invariance is an extremely stringent criterion that may not apply in certain research contexts, especially when more than two groups are being compared, when groups are from highly heterogeneous cultural backgrounds (De Beuckelaer & Swinnen, 2011; Horn, 1991), or when measures have been translated into different languages (Schmitt & Kuljanin, 2008). For example, a number of recent cross-cultural studies (Joshi et al., 2014; Malham & Saucier, 2014) evaluating measurement invariance of an instrument have failed to establish full invariance. Interpreted in this context, the partial measurement invariance established for the two-factor LMSQ model is impressive and allows for meaningful cross-cultural evaluation of LMSQ's factor means and associations with other variables. Though encouraging, readers should note the caveat that a one-factor model is preferred for certain countries.

In general, the factor means of the LMSQ subfactors did not differ substantially from those from the US sample. In the spirit of exploration, it seems that some countries (i.e., Croatia and Italy) exhibited lower means on the looming factors than the US. One possible reason might be that the samples in these two countries were community volunteers and older participants might show lesser susceptibility to a looming cognitive style compared to their younger counterparts. In the case of Italy, for instance, individuals from the community tend to report lower anxiety and depression symptoms compared to college students (Sica & Ghisi, 2007). In addition, it is very likely that, compared to their older counterparts, younger adults may fear more social failures and physical threats. However, we were unable to confidently rule out the possibility of cultural factors (e.g., response sets) at play as well. More research is needed to clarify this issue.

The current study replicates and extends the González-Díez et al.'s (2014) conclusion showing measurement invariance across gender groups in Spain. In that study, scalar invariance was not evaluated, hence the extent to which men and women differed on the latent factor means was unknown. Here, full measurement invariance of the LMSQ across gender was established; implying that men and women across different countries ascribe the same meanings to, and respond similarly to, the LMSQ items. Although the latent factor means across gender were considered different by the chi-square difference test, the CFI difference test indicated otherwise. We interpret this result as indicative of gender differences that are too small to have substantive practical or clinical significance. Nonetheless, we acknowledge that other studies have documented females having higher LCS than males (González-

Díez et al., 2014), which might indicate that LCS might help to explain females' greater risk for anxiety and depressive disorders (McLean, Asnaani, Litz, & Hofmann, 2011; Piccinelli & Wilkinson, 2000) in some subgroups. It also remains to be determined whether gender differences are significant in clinical populations.

Findings from the TSSEM procedure suggest that depression symptoms are uniquely predicted by social looming, and to a lesser extent, by physical looming. Looming social threats such as an impending social rejection might have implications for mood disturbances, particularly so when participants have had prior experiences of such threats (Ayduk, Downey, & Kim, 2001). As expected, the role of looming physical threats on depression symptoms is less salient as the impending harm to one's physical well-being likely activates the fear response system to mitigate environmental threats. Conversely, the contributions of the two looming factors on anxiety appear comparable, further bolstering the idea that both components are critical in the etiology of anxiety symptoms. In general, the LMSQ factors exhibit good construct validity as they possess non-redundant associations to emotional symptoms, supporting the theoretical postulation that they might represent species-wide cognitive risk mechanisms.

The looming cognitive style was initially theorized as a cognitive vulnerability factor mainly for anxiety (but not depressive) symptoms, and while empirical evidence supported this (e.g., Adler & Strunk, 2010; Reardon & Williams, 2007; Riskind et al., 2000, 2006, 2007), recent evidence has shown that it can have relations with depression (Kleiman & Riskind, 2012; Levin et al., 2007; Riskind et al., 2013; Tzur-Bitan et al., 2012). In line with the latter findings, the current data suggest that the association of LCS with depression is comparable to that of anxiety. Supplementary analyses were done to explore the plausible reasons for the comparable predictability for anxiety and depression in our samples. Gender did not moderate the relation between LMSQ and symptoms. Sample characteristic (i.e., community versus student samples), however, was a likely moderator. Averaged effect sizes obtained from meta-analyses done on community (i.e., Croatia and Italy) versus student samples separately revealed that community (or older) participants exhibited a stronger link between social looming and depression, compared to anxiety.⁵

As previously suggested, when threat is uncertain – and there is still a possibility of evading harm – anxiety might be the strongest reaction. However, when one perceives that harm cannot likely be evaded, or already happened, depression should also be likely. The supplementary finding in the preceding paragraph is consistent with this notion. We

⁵ For community participants, the relation between physical looming and anxiety was 0.25 but was 0.26 for depression; the difference in coefficients not statistically significant. The relation between social looming and anxiety was 0.23 but was 0.34 for depression; the difference was significant at $z = 3.95, p < 0.001$. Conversely, for student participants, the relation between physical looming and anxiety was 0.27 but was 0.20 for depression; the difference was significant at $z = 2.86, p = 0.004$. The relation between social looming and anxiety was 0.29 but was 0.27 for depression; the difference in coefficients not statistically significant. Although physical looming predicted anxiety more strongly than depression in the student samples, social looming predicted depression more strongly than anxiety in the community samples.

speculate that for older adults, if they still experience distress with respect to pending social rejections at their age, it would mean that they have had prior experiences with such threats and have over time perceive them to be unavoidable. The notion that depression is likely when the threat has already happened or unlikely to be evaded has been supported among leukaemia patients (Levin et al., 2007), as well as among college students with elevated depressive cognitive styles (Kleiman & Riskind, 2012).

There are other mechanisms potentially at play that might modulate the symptom specificity of the LCS. The nature and number of negative life events that individuals face may also conceivably determine the extent to which the LCS predicts depression. For example, the depressive cognitive style questionnaire scores negative events according to the degree to which they may cause hopelessness due to the individuals' perceptions of the pervasiveness and permanence of the causes of the negative events (i.e., their globality and stability) and their impact. Although our present samples did not assess negative life events, this variable might be an important moderator. It might be that when individuals experience negative events of limited globality and stability, the LCS may primarily predict anxiety. Conversely, when individuals face events of greater global/stable influence and negative impact, LCS may predict depression as well. Another possibility is that the LMSQ might predict less symptom specificity of anxiety and greater comorbidity of symptoms among samples that are less able to differentiate between specific emotions (i.e., low on "emotion granularity") and to indiscriminately label all specific emotions as "bad" (Tugade, Fredrickson, & Barrett, 2004). The extent to which specificity to anxiety is found may depend on sampling differences in emotion granularity.

The current results should be interpreted in light of several methodological limitations. First, although we have adopted the two-factor model in the current paper, the observation that a one-factor model is preferred in three countries (i.e., Canada, Croatia, and Serbia) suggests that there may still be cultural differences in the structure of LMSQ. We are unsure at this point what could account for these differences and hence future research should aim to clarify this issue. Data from a larger sampling of countries would be instrumental to further illuminate LMSQ's factorial structure. Second, the cross-cultural data were obtained via a convenient sample of countries in which the local researchers had used the LMSQ. Future research should consider a more systematic sampling of countries with more demographic data (e.g., socio-economic status) included. Third, the self-reports of looming cognitive style and symptoms present the problem of common method variance and use of other assessment methods such as structured interviews for assessing symptom severity would be better. Fourth, despite the heterogeneity of anxiety-related syndromes, we could only limit our analyses to nonspecific anxiety symptoms. The small number of countries that have included measures of specific forms of anxiety (e.g., obsessive-compulsive symptoms, social anxiety) did not allow for meaningful synthesis of data. Future research should evaluate the summarized magnitude of associations between the looming factors and other forms of anxiety when more data are available.

The fifth limitation was that local researchers in Japan and Nepal had modified the LMSQ scenarios that precluded the use of their data in the comprehensive examination of measurement invariance across countries. However, as the extent of modification was small (one out of six scenarios), the associations of the looming factors with other variables should not be excessively distorted. Also, some country data were obtained without proper back-translation procedures. Nonetheless, the psychometric properties of the LMSQ in these languages were good. Sixth, generalizability of the present findings is limited to nonclinical samples and the measurement properties of the LMSQ of clinical samples in cross-cultural contexts are unknown. In addition, our samples were not representative of the populations of the respective countries, so one should be cautious about generalizing these results to all members within these countries. Still, many cross-cultural studies commonly recruit college students (e.g., Arrindell et al., 2003,

2013; Radomsky et al., 2014; Sica, Taylor, Arrindell, & Sanavio, 2006). In fact, the use of students ensures that the cultural groups are approximately matched on extraneous demographic variables such as gender composition and occupational status.

A clinical implication arising from the presenting findings is that the LMSQ can be used to assess looming vulnerability reliably in different cultural and gender groups. As such, clinicians are encouraged to include the LMSQ in their routine assessment of emotional disorders so as to isolate the possibility of a looming vulnerability. Clinicians can then help their clients modify features (e.g., distance, incoming speed) implicated in their mental simulation of escalating threats as a component of intervention (see Riskind & Williams, 1999).

This research represents a first attempt to evaluate the measurement invariance of the LMSQ cross-culturally. In spite of the difficulties in achieving full measurement invariance across eight distinct cultures, the ability of the LMSQ test scores to exhibit partial scalar invariance is encouraging. Invariance of the LMSQ test scores cross-culturally opens up new avenues for its use in other cultural groups and permits meaningful interpretations regarding the correlations of the LMSQ factors with external variables. Full measurement invariance across gender confers strong confidence in the LMSQ yielding equal measurement properties for men and women. Evidence for the construct validity of the LMSQ factors in predicting depression and anxiety symptoms is encouraging and supports the idea of LCS as a species-wide cognitive mechanism. In conclusion, the use of the LMSQ in different cultures is promising and should be encouraged, so as to advance the generalizability of the looming cognitive vulnerability theory.

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