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Adaptation of the Climate Anxiety Scale in Indonesian version: The sample of young adults

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Abstract: The negative emotional impact of climate change has been reported in numerous studies. However, the research on the topic in Indonesia is limited, partly due to the absence of a valid scale relating to the Indonesian context. The study aims to adapt and evaluate the psychometric properties of the Climate Anxiety Scale. The adaptation of the scale into Indonesian concerned the International Translating Commission. The study involved 306 young people aged 18 to 35 (M= 21.01, 80.4% female) from February to June 2023. Psychometric property analysis consisted of internal consistency, Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA). The results indicate satisfactory reliability (Cronbach's $\alpha = .91$; McDonald's $\omega = .91$). Although most items (apart from FI5) behaved similarly to the original 2-factor structure based on EFA, they did not achieve a reasonable fit based on CFA. Therefore, the authors carefully made modifications based on modified indices of the 2-factor structure to achieve reasonable local fit measurements. The authors recommend examining the original structure using different sample categories and approaches (e.g., criterion validity) in the Indonesian sample.

Keywords: adaptation; Climate Anxiety Scale; factor analysis; internal consistency

Abstrak: Dampak emosi negatif akibat perubahan iklim telah banyak ditemukan dalam penelitian. Sayangnya, penelitian pada topik ini di Indonesia masih tidak banyak ditemui, salah satunya karena tiadanya skala yang valid pada konteks Indonesia. Penelitian ini bertujuan untuk mengadaptasi dan mengevaluasi properti psikometri *Climate Anxiety Scale*. Adaptasi skala ke dalam Bahasa Indonesia mengacu pada *the International Translating Commission*. Penelitian ini melibatkan 306 individu muda berusia 18 hingga 35 tahun (M=21,01, 80,4% perempuan) pada Februari - Juni 2023. Data diperlakukan sebagai ordinal. Analisis properti psikometri meliputi konsistensi internal, analisis faktor eksploratori (EFA) dan analisis faktor konfirmatori (CFA). Hasil menunjukkan reliabilitas yang memuaskan (Cronbach's $\alpha = 0{,}91$; McDonald's $\omega = 0{,}91$). Walaupun sebagian besar butir berperilaku mirip dengan struktur 2 faktor asli (kecuali FI5) berdasarkan EFA, namun kesesuaian model yang dapat diterima tidak diperoleh berdasarkan CFA. Oleh karena itu penulis dengan hati-hati melakukan modifikasi berdasarkan indeks modifikasi dan memperoleh struktur dua faktor model yang sesuai berdasarkan kesesuaian lokal. Penulis merekomendasikan pemeriksaan struktur awal pada kategori sampel dan pendekatan (misal: validitas kriteria) yang berbeda pada sampel Indonesia.

Kata Kunci: adaptasi; *Climate Anxiety Scale*; analisis faktor; konsistensi internal

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Introduction

Climate change impacts not only physical health issues but also mental ones. Research on the link between climate change and mental health has been conducted (Berry et al., 2010; Bourque & Willox, 2014; Cianconi et al., 2020; Usher et al., 2019), and it is evident that climate change causes negative feelings, which can lead to various psychological conditions. The emergence of related mental health problems can occur directly or indirectly, both in the short and long term (Berry et al., 2010; Bourque & Willox, 2014). For example, floods, landslides, and tornadoes can directly cause anxiety and post-traumatic stress for the victims. In the longer term, the damage can force people to be displaced and trapped in uncertainty, further exacerbating their psychological distress.

Psychological issues related to worsening climate and environmental conditions range from anxiety and depression (Clayton & Karazsia, 2020); to post-traumatic stress and suicidal tendencies (Cianconi et al., 2020), insomnia and self-rated mental health (Ogunbode et al., 2023), and reduced individual well-being (Ogunbode et al., 2022). Such conditions are even worse in vulnerable groups, namely those whose livelihoods depend on nature (e.g., fishermen and farmers) (Bourque & Willox, 2014; Coffey et al., 2021); people from low socioeconomic groups; women; and young individuals (Cianconi et al., 2020; Clayton et al., 2023; Coffey et al., 2021). These studies were conducted in various country contexts and obtained fairly consistent results.

Young people are of particular concern, as they will be taking responsibility for the future of life on the planet, yet they are also among those most affected by worsening climate change. This generation is experiencing anxiety and fears for the future (Ágoston et al., 2022; Hickman et al., 2021; Wu et al., 2020) due to their perception of a bleak future if climate change is not addressed. Hickman et al.'s (2021) study of ten countries with 10,000 participants found that young people were experiencing negative emotions due to climate change, such as feeling worried, scared, angry, sad, anxious, helpless, hopeless, and guilty. Several other studies have obtained similar results, in which young people in the Philippines, India, and Nigeria respectively were found to be displaying higher levels of climate anxiety (Clayton et al., 2023; Diffey et al., 2022; Galway & Field, 2023).

Indonesia is a developing country, similar to those studied in Clayton et al.'s (2023) research, so it is assumed that the country's youth are also experiencing the psychological impacts of climate change. A survey by Leiserowitz et al. (2021) on Facebook users in 31 countries found that 45% and 34% of the Indonesian population were worried about climate change at extreme and moderate levels, respectively. To the author's knowledge, no other study has examined the impact of negative emotions due to climate change in Indonesia.

Commonly-used terminology to refer to the state of anxiety caused by the climate crisis and the threat of environmental disasters include eco-anxiety, climate distress, climate change anxiety, and climate anxiety (Wu et al., 2020). In this study, reference is made to the work of Clayton and Karazsia (Clayton & Karazsia, 2020), and the term 'Climate Change Anxiety' (CAS) is used. It refers to anxiety related to the perception of climate change, even amongst those who are not directly at risk of experiencing disasters due to climate change (Clayton & Karazsia, 2020). Furthermore, climate change has attributes that mean it is considered as an environmental stressor: 1) it is a real threat; 2) it is happening and growing; 3) it is uncertain; 4) it is happening globally; and 5) it is a major, significant threat.

The clear issue of climate anxiety is not reflected in the amount of research on the topic. In Indonesia specifically, few researchers have shown interest in the issue. This is partially due to the lack of measurement instruments adapted to the Indonesian language and context. Research related to climate anxiety mainly originates from developed Western countries, which have different characteristics compared to Indonesia. In the research, the instruments or scales that measure anxiety related to the climate or environment have been mostly developed in the context of Western society, meaning they are less suitable for the context of Indonesian society. Relatively few measurement instruments exist related to the topic of climate anxiety. Some of the currently used measurement instruments are the Eco-anxiety Scale, which has been validated in the Turkish context (Uzun et al., 2022); the Climate Change Worry Scale (Stewart, 2021); the Hogg Eco-Anxiety Scale (Hogg et al., 2021); and the Climate Anxiety Scale (Clayton & Karazsia, 2020).

For this study, CAS was preferred for two reasons: 1) it has been the one most widely adapted to various contexts compared to other similar tools; 2) it has been widely adapted to contexts similar to Indonesia. The Climate Anxiety Scale instrument developed by Clayton and Karazsia (2020) is the most widely used and has been adapted in several countries, such as France (Mouguiama-Daouda et al., 2022); Poland (Larionow et al., 2022); the Philippines (Simon et al., 2022); Korea (Jang et al., 2023); and with German-speaking participants (Wullenkord et al., 2021). The psychometric properties of the measurement were good in almost all these studies.

Clayton and Karazsia (2020) developed the CAS to measure psychological responses to climate change, consisting of two subscales that assess cognitive or functional impairment. The conceptualization of the construct is a measure of stress or anxiety, an affective response to environmental circumstances (Clayton & Karazsia, 2020). It consists of two dimensions: cognitive-emotional impairment and functional impairment (Clayton & Karazsia, 2020).

Although the subscales are closely correlated and can be combined to assign an overall "climate change anxiety" score, some differences in the patterns of correlation have been shown (Clayton & Karazsia, 2020). According to Clayton and Karazia's study, cognitive and emotional impairment in response to climate change is reflected in rumination, difficulties in sleeping or concentrating, and nightmares or crying, while functional impairment with high ratings indicates that concern about climate change is interfering with a person's ability to work or socialize (Clayton & Karazsia, 2020). Along with the subscales of behavioral engagement and personal experience of climate change, the confirmatory factor analysis resulted in a good to acceptable or reasonable fit with the observed data (Clayton & Karazsia, 2020).

The psychometric properties of the measure have mostly good reliability, but vary in validity. In previous CAS validation studies, varying results have been obtained. In some countries, such as France (Mouguiama-Daouda et al., 2022), the Philippines (Simon et al., 2022), and Australia (Feather & Williams, 2022), it has been possible to replicate the original factor structure with at least a reasonable global fit. Some researchers have proposed alternative CAS models as the model fit indices for the 2-factor have been mixed, with some fit indices indicating an unsatisfactory fit, but others indicating a satisfactory or good one, such as in the Australian context (Hogg et al., 2023) and in Poland (Larionow et al., 2022). In the context of a German-speaking country (Wullenkord et al., 2021), the original factor structure could not be replicated.

Climate anxiety scales have been adapted to several languages, such as French (Mouguiama-Daouda et al., 2022), German (Wullenkord et al., 2021), Polish (Larionow et al., 2022), Filipino (Simon et al., 2022), and Korean (Jang et al., 2023). However, the authors have not found any Climate Anxiety Scales or similar instruments adapted to Indonesian. This study is, therefore, believed to be the first to adapt the Climate Anxiety Scale to the Indonesian language and context. It is important that this study be conducted, considering that Indonesia is a country that is prone to disasters caused by climate change. Moreover, the validity results of the psychometric properties of the Climate Anxiety Scale vary according to the context. This study aims to adapt the Clayton and Karazsia (Clayton & Karazsia, 2020) Climate Anxiety Scale into Bahasa Indonesia, and evaluate its psychometric properties to determine the validity and reliability of the instrument.

Methods

Participants

All the participants (n = 306; mean age = 21.01, 80.4% female) were Indonesian. To be eligible, the participants had to be aged 18 to 35. Regarding their highest level of education, approximately 69% reported having a high school diploma, 26.5% were undergraduate, 4.2% were masters, and 0.3% were educated to doctoral level. The sample size meets the minimum sample size (>273) for DWLS models (calculated from the formula 1.5p (p+1); p >12; p = number of observed variables), as recommended by Jöreskog and Sörbom (Nye & Drasgow, 2011).

Regarding data collection from respondents, this study has met the ethical test by the Faculty of Nursing, Universitas Airlangga, Surabaya, Indonesia, based on Certificate No. 2806-KEPK.

Procedure

The Climate Anxiety Scale adaptation process was conducted in two stages: the translation into Bahasa Indonesia and the psychometric evaluation stage. The procedure section describes the adaptation process into Bahasa Indonesia in detail, while the psychometric evaluation stage is explained in depth in the data analysis section.

The adaptation of the Climate Anxiety Scale into Bahasa Indonesia followed the guidelines of the International Test Commission (2017). The pre-condition phase began by requesting permission from Prof. Clayton to adapt the scale. Subsequently, the research team and expert panel discussed the definition, content, and constructs, adjusting these to suit the target population. The process continued with the adaptation phase, which consisted of five stages: 1) translation of the scale into Bahasa Indonesia, which was conducted independently by a translator (with an IELTS score higher than 7) and the first researcher, both of whom have a background in psychology; 2) meeting of a reconciliation panel, where the translator and the first researcher discussed the translation of the original scale to obtain a forward translation; 3) the forward translation scale was back-translated into the original language by two independent translators with a good level of English (IELTS scores higher than 7) and the Indonesian context; 4) a panel discussion, during which all the scales (original, forward translation, and backward translation) were discussed to obtain a pre-final translation to be tested for readability; and 5) a readability test conducted with a number of 38 participants who had similar characteristics to the target population. Subsequently, a confirmation phase was conducted to test the scale on the target population for further psychometric testing.

Measurement

Climate Anxiety Scale (CAS)

The CAS (Clayton & Karazsia, 2020) was designed to measure the emotional responses associated with awareness of climate change. It is a 13-item self-report questionnaire consisting of eight items on cognitive-emotional impairment and five on functional impairment, with no reverse-coded items. The participants responded to the items on a scale of 1-5 (1: never; 2: rarely; 3: sometimes; 4: often; 5: almost always). Unlike previous studies, the authors treated the data ordinally and conducted the analysis accordingly.

Sample items included: "Thinking about climate change makes it difficult for me to concentrate" (cognitive-emotional impairment), and "My concerns about climate change make it hard for me to have fun with my family or friends" (functional impairment). The scale has not been previously adapted to Indonesian, so reports on the psychometric properties from previous studies are unavailable.

Data Collection

The translated Climate Anxiety Scale was distributed for online data collection through a Google form. The research team created a flyer containing a link to the scale and the participant inclusion criteria, which were then distributed through social media (WhatsApp and Instagram) to recruit potential participants. Those who were willing to participate in the study filled in the provided scale link. Data collection was conducted during the period February to June 2023.

Data Analysis

Software

Several software packages were employed for the data analysis process. Jamovi version 2.3, an online analysis tool (The Jamovi Project, 2023) was used to calculate reliability (Cronbach's α, McDonald's ω, and item-total correlation). Mardia's test and the factor determination (parallel analysis and MRFA) number were calculated by R (Posit Team, 2023; R Core Team, 2023) with a package consisting of MVN (Version 4.2.3), psych (Version 2.3.3) and EFA.MRFA (Version 1.1.2). Exploratory factor analysis (EFA) was conducted with FACTOR version 12.04.01 (Lorenzo-Seva & Ferrando, 2006) with polychoric correlation, robust DWLS factor extraction, and direct *oblimin* rotation. Confirmatory factor analysis (CFA) was conducted using Mplus (Muthén & Muthén, 1998) version 8.3, with estimator WLSMV (the data treated as ordinal) and estimator MLR (the data treated as continuous).

Reliability

Reliability refers to the consistency of a measure (Price et al., 2015). This study employed internal consistency and split-half methods with the satisfactory reliability criteria used above .70 (for Cronbach's α and McDonald's ω) and .80 (for the split-half method). It refers to the consistency of people's responses to an item on a multiple-item measure (Price et al., 2015). The authors conducted split-half correlation, Cronbach's α, and McDonald's ω calculations. In addition, the authors provided information on item-total correlation to obtain information on each item.

Exploratory Factor Analysis

EFA attempts to identify the smallest number of hypothetical constructs that can parsimoniously explain the covariation observed among a set of measured variables (Watkins, 2018). The authors employed two techniques, Bartlett's test of sphericity (1950) and the Kaiser-Meyer-Olkin (KMO) test (1974), to determine if the data were adequate for factor analysis. Two methods to determine the number of factors, parallel analysis (Horn, 1965) and Minimum Rank Factor Analysis (MRFA) (Berge & Kiers, 1991) were employed. Parallel analysis is intended to indicate the quality of performance (Zwick & Velicer, 1986) to determine the number of factors (Fabrigar et al., 1999), while MRFA has been shown to be a good choice for the identification of the number of common factors (Timmerman & Lorenzo-Seva, 2011) that yield optimal communalities (Shapiro & ten Berge, 2002). Therefore, the number of factors will be determined based on both sets of results, with consideration of parsimony and theoretical convergence.

The polychoric correlation coefficient is a measure of association for ordinal variables (whose values can only be compared in terms of their ordering) (Ekström, 2011). It was used in this study together with the estimator robust Diagonally Weighted Least Squares (DWLS) and direct *oblimin* rotation (detailed configuration for clever start was set to none). DWLS provides more accurate parameter estimates and a model fit that is more robust to variable type and non-normality (Mîndrilă, 2010). *Oblimin* rotation, one of the most popular oblique rotation methods (Watkins, 2018), allows correlation between the produced factor solutions, hence providing a more accurate and realistic representation of how constructs are likely to be related to one another (Fabrigar et al., 1999). A total of 13 measure items were used for the analysis.

The criteria for determining factor adequacy were established a priori. The critical value (CV) for loadings by taking sample size into account was calculated according to Norman and Streiner (1994), resulting in ≥.30 as the cutoff. Salient items were then described as those with factor loadings ≥.30. The description of the fit measures to be reported consisted of the comparative fit index (CFI); the Tucker-Lewis index (TLI, also known as the non-normed fit index; and the root mean square error of approximation (RMSEA), as provided by default by the software, and chi-square (χ^2) for additional information. The minimum criteria for model fit are CFI and NNFI ≥.90, and RMSEA ≤.08.

Confirmatory Factor Analysis

Confirmatory factor analysis is a type of structural equation modeling (SEM) that deals specifically with measurement models (the relationships between observed measures and latent variables) (Brown, 2015). It is also used to verify the number of underlying dimensions of the instrument (factor) and the pattern of item-factor relationships (factor loadings) (Brown, 2015). The authors used an adjusted weighted least squares mean and variance (WLSMV) estimator, a robust weighted least squares estimator using a diagonal weight matrix (Muthén & Muthén, 2019). The WLSMV estimator provided by Mplus appears to give the best option for CFA modeling with categorical data (Brown, 2015). Lloret et al. (2017) showed that Mplus with a non-linear approach using the WLSMV robust estimation method presents no problems. Brauer et al. (2023) proposed that it could be fruitful to analyze data generated by responses to ordered categorical rating scales with robust maximum likelihood (MLR) and WLSMV approaches and transparently report findings and their convergence across methods. Hence, for additional information, the authors ran CFA with an MLR estimator. The authors treated the data as categorical in the WLSMV estimator, and since Mplus does not provide fit indices for MLR estimation with categorical data, the authors treated the data as continuous in the MLR estimation.

Results

Adaptation of the Climate Anxiety Scale to Bahasa Indonesia

Based on the forward-backward translation process, three items (CEI6, FI2, and FI4) underwent word changes from the forward translation. In the panel discussion process, it was decided to change these three items to make them more appropriate. After the forward-backward translation items were received, a readability test was conducted on 38 students who had similar characteristics to the participants' criteria. Based on this test, several items underwent word changes and sentence adjustments as the original versions were considered relatively difficult to understand in the Indonesian context. The changes made were: 1) substituting the word "*ku*" in items CEI1, CEI2, and FI5 to "*saya*" and 2) changing the word "*mimpi*" to "*bermimpi*" in item CEI3. Table 1 shows example items from the scale adaptation process.

Data Exploration

The data distribution for single variable examination with skewness and kurtosis had varied cutoffs. Hair et al. (2009) state that skewness values falling outside the range of -1 to 1 indicate a significantly skewed distribution, while Kim (2013) proposes that an absolute skew value higher than 2 and absolute kurtosis (proper) higher than 7 may be used as reference values for determining significant non-normality for sample sizes greater than 300. As shown in Table 2, the skewness of CEI1 and FI5 are above 1. On the other hand, the results of Mardia's test for the multivariate normal distribution showed that the data did not meet the assumption (Mardia's skewness statistics = 1407.12; $p < .01$ and Mardia's kurtosis statistic = 24.22; $p < .01$). Therefore, the authors conclude that the data did not meet the assumption of normal distribution.

Table 1

Example of Translation Changes in the Climate Anxiety Scale

No	Original Item	Forward Translation	Backward Translation	Final Item
CEI1	Thinking about climate change makes it difficult for me to concentrate.	*Memikirkan perubahan iklim <u>membuatku</u> sulit berkonsentrasi.*	Thinking about climate change makes it hard for me to concentrate. Thinking about climate change makes it difficult for me to concentrate.	*Memikirkan perubahan iklim <u>membuat saya</u> sulit berkonsentrasi.*
CEI2	Thinking about climate change makes it difficult for me to sleep	*Memikirkan perubahan iklim <u>membuatku</u> susah tidur.*	Thinking about climate change makes it hard for me to sleep. Thinking about climate change makes it difficult for me to sleep.	*Memikirkan perubahan iklim <u>membuat saya</u> susah tidur.*
CEI3	I have nightmares about climate change	*Saya <u>mimpi</u> buruk tentang perubahan iklim.*	I have nightmares about climate change.	*Saya <u>bermimpi</u> buruk tentang perubahan iklim.*
CEI6	I go away by myself and think about why I feel this way about climate change.	*Saya <u>keluar sendiri dan merenungkan</u> mengapa saya merasa seperti ini tentang perubahan iklim.*	I go out alone and contemplate why I feel this way about climate change. My worries about climate change make it difficult for me to have fun with my family and friends.	*Saya <u>menyendiri dan memikirkan</u> mengapa saya merasa cemas tentang perubahan iklim.*
FI2	I have problems balancing my concerns about sustainability with the needs of my family	*Saya <u>kesulitan</u> menyeimbangkan keresahan saya mengenai keberlanjutan dengan kebutuhan keluarga saya*	I have a hard time balancing my concerns about sustainability with my family's needs. I have a hard time balancing my concerns about sustainability with the needs of my family.	*Saya <u>memiliki masalah dalam</u> menyeimbangkan keresahan saya mengenai keberlanjutan dengan kebutuhan keluarga saya.*
FI4	My concerns about climate change undermine my ability to work to my potential.	*Keresahan saya tentang perubahan iklim melemahkan kemampuan saya untuk <u>bekerja secara maksimal</u>.*	My concern about climate change weakens my ability to perform at my best level. My anxiety about climate change undermines my ability to perform at my full potential.	*Keresahan saya tentang perubahan iklim melemahkan kemampuan saya untuk <u>bekerja sesuai potensi.</u>*
FI5	My friends say I think about climate change too much.	*<u>Teman-temanku</u> mengatakan <u>aku</u> terlalu memikirkan perubahan iklim*	My friends say I think too much about climate change.	*<u>Teman-teman saya</u> mengatakan <u>saya</u> terlalu memikirkan perubahan iklim.*

Table 2

Descriptive Statistics and Item-rest Correlation

Item	Mean	Skewness	Kurtosis	Item-rest Correlation
CEI1	2.38	0.0770	-.496	.500
CEI2	2.15	0.5143	-.365	.657
CEI3	1.75	1.0475	.380	.628
CEI4	1.82	0.8804	-.193	.657
CEI5	2.36	0.3613	-.787	.492
CEI6	2.07	0.6382	-.570	.714
CEI7	1.86	0.8280	-.187	.614
CEI8	2.19	0.4307	-.800	.701
FI1	2.22	0.5091	-.789	.598
FI2	2.37	0.4856	-.693	.587
FI3	2.05	0.7404	-.155	.662
FI4	1.95	0.8127	-.134	.660
FI5	1.61	1.1640	.258	.572

Reliability

The split-half method of estimating internal consistency, involving correlation of the scores of odd and even items, resulted in a correlation coefficient of .87. For each subtest, Cronbach's α and McDonald's ω were .87 for cognitive-emotional impairment. Regarding functional impairment, Cronbach's α was .83, and McDonald's ω was .84. For one scale, the internal consistency of CAS in this study (Cronbach's α = .91; McDonald's ω = .91) met the satisfactory level of reliability in the early stages of construct validation research, as recommended by Nunnally and Bernstein (1994), Cronbach's α should be above .70. Moreover, in the level of item, the range of item-rest correlation was .492 to .714 (all above .3). The results therefore provide evidence that CAS in this study met the requirements of measurement reliability.

Exploratory Factor Analysis

The KMO result was .896, which according to Kaiser (1974) is categorized as meritorious. Bartlett's test of sphericity was significant, with χ^2 (78) = 1982, $p < .001$, which means that the rejection of the hypothesis is taken as an indication that the data are appropriate for analysis (Dziuban & Shirkey, 1974). The authors' data were adequate for factor analysis.

Based on the parallel analysis (see Figure 1), the actual eigenvalues for the first four factors were greater than the corresponding simulated eigenvalues. In addition, based on the MRFA (see Figure 2), the real data for the first factors were greater than the corresponding mean of random and 95 percentile percentage of explained common variance. The evidence from the parallel analysis and MRFA indicates that 13 items of self-report materialism measurement could be summarized by 1 up to 4-factor.

As can be seen in Table 3, all the models have CFI and NNFI >.90, while model 3 and 4 have RMSEA <.08. The 3-factor model seems to have the best fit and parsimony compared to the others, but there is a factor that consists of only 2 items (< 3 items on a factor indicating over-factoring). As for the 2-factor model, the RMSEA was > .08, which means unacceptability.

The inter-factor correlation between F1 and F2 was .619. As shown in Table 4, all the items are salient, with no cross-loading. The highest communality was in FI3, and it might underlie the factor loading was above 1 on F2, so it could be quite challenging to interpret the result. The use of direct *oblimin* rotation, which is known as oblique, might have been the reason for such a result. The lowest communality was in CEI1. FI5 had higher factor loadings on F1 compared to F2, indicating findings which differ from the theory.

Table 5 shows the rotated loading matrix for the 3-factor model. Inter-factor correlations between F1 and F2, F1 and F3, F2 and F3 were .565, .579, .583 respectively. The highest communality was the same as in the 2-factor model (FI3), while the lowest communality for the 3-factor model was FI1, since CEI1 was loaded to F3 along with CEI2. F15 also had higher factor loadings on F1, even in the 3-factor model.

Figure 1

Number of Factor Determinations based on Parallel Analysis

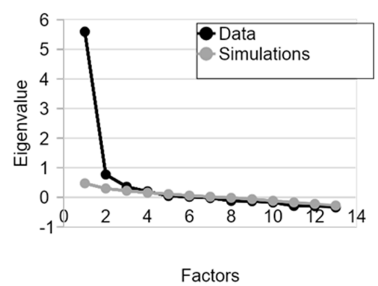


Figure 2

Number of Factor Determinations based on MRFA

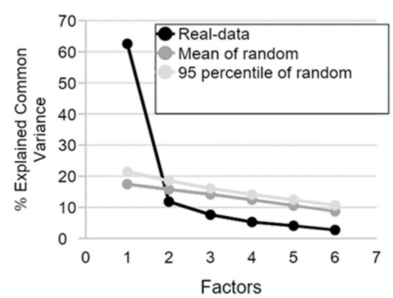


Table 3

Model Summary of EFA

Model	Variance explained (%)	χ^2/df	CFI	NNFI	RMSEA (95% CI)
1	54.69	337.534/65	.960	.966	.117 (.084 - .134)
2	61.05	188.100/53	.983	.976	.091 (.067 - .106)
3	66.04	95.995/42	.993	.988	.065 (.046 - .075)
4	68.73	70.589/32	.995	.988	.063 (.027 - .073)
Rule of thumb for acceptable model (Hogg et al., 2023; Hu & Bentler, 1999)			≥.90	≥.90	≤.08

Note: polychoric correlation, DWLS, and direct *oblimin* rotation with clever start set as none.

Table 4

Rotated Loading Matrix for the 2-Factor Model

Item	F1	F2	h^2
CEI1	**0.375**	0.291	0.360
CEI2	**0.574**	0.257	0.578
CEI3	**0.764**	0.045	0.627
CEI4	**0.838**	-0.014	0.689
CEI5	**0.859**	-0.230	0.547
CEI6	**0.810**	0.061	0.722
CEI7	**0.634**	0.134	0.526
CEI8	**0.633**	0.196	0.592
FI1	0.237	**0.541**	0.507
FI2	0.204	**0.581**	0.526
FI3	-0.054	**1.002**	0.940
FI4	0.086	**0.842**	0.806
FI5	**0.569**	0.210	0.515
% of Explained Variance	37.18	23.87	

Notes: The DWLS extraction method was used in combination with direct-*oblimin* rotation. h2=communality. Salient items with factor loading ≥ .3 were shown in bold.

Table 5

Rotated Loading Matrix for the 3-Factor Model

Item	F1	F2	F3	h^2
CEI1	-0.041	0.064	**0.748**	0.583
CEI2	0.083	0.006	**0.874**	0.862
CEI3	**0.594**	0.030	0.260	0.629
CEI4	**0.685**	-0.009	0.224	0.689
CEI5	**0.880**	-0.109	-0.100	0.599
CEI6	**0.788**	0.152	-0.021	0.757
CEI7	**0.522**	0.144	0.159	0.526
CEI8	**0.554**	0.228	0.096	0.598
FI1	0.205	**0.561**	0.028	0.513
FI2	0.245	**0.648**	-0.108	0.559
FI3	-0.063	**1.010**	-0.003	0.948
FI4	0.009	**0.819**	0.118	0.806
FI5	**0.422**	0.189	0.227	0.517
% of Explained Variance	28.12	22.98	14.94	

Notes: The DWLS extraction method was used in combination with direct-*oblimin* rotation. h2=communality. Salient pattern coefficients ≥.3 were shown in bold.

Confirmatory Factor Analysis

As shown in Table 6, all the models for each estimator failed the exact-fit (global fit) test. The Chi-square ($\chi 2$) results were significantly different (p-value= .0000), which indicates that the model did not fit the data well. Moreover, according to van Zomeren et al. (2013), the ratio of Chi-square and degree of freedom (χ 2/df) showing an excellent fit is indicated when the $\chi 2$/df ratio is below 2, whereas a good fit is indicated when this ratio is between 2 and 3. In this case, none of the results indicates a good or excellent fit. For all the presented models, RMSEA clearly fails the local fit, whereas SRMR passes. The CFI and TLI of the 2- and 3-factor models (WLSMV) passed, while the remainder failed.

Since the authors found that data based on EFA showed differences compared to the theory, the authors ran CFA with several modifications. Based on modification indices (M.I.) and substantive justification, the model was revised and fit to the data again, in the hope of improving its goodness of fit (Brown, 2015). The authors first used the results of the EFA 3-factor model with CEI1 and CEI2 loaded to F3 to conduct CFA. Second, the authors employed a CFA 3- and 2-factor models, with FI5 was loaded to CEI. Finally, the authors ran CFA with several specifications according to modification indices based on the results of the CFA 2-factor model with the WLSMV estimator.

All the models failed the exact-fit (global fit) test; the Chi-square (χ^2) result was significantly different (p-value= .0000), indicating that the model did not fit the data well (see Table 7). Based on the ratio of Chi-square and degree of freedom, the 2-factor model with specifications of FI5 on CEI, and residual correlated items (CEI1 & CEI2, FI3 & FI4, CEI5 & CEI6) were between 2- and 3-factor, which indicated a good fit (van Zomeren et al., 2013). This model also passed the local fit measures (CFI, TLI, RMSEA, SRMR) based on the rules of thumb.

Table 6

Summary of the Model Fit Parameters

Model	Estimator	χ^2/df	CFI	TLI	RMSEA (90% CI)	SRMR
1 Factor	MLR	357.029/65	.789	.747	.121 (.109 - .134)	.073
2 Factor	MLR	241.768/64	.872	.844	.095 (.083 - .108)	.074
3 Factor	MLR	228.860/62	.880	.849	.094 (.081 - .107)	.073
1 Factor	WLSMV	635.979/65	.883	.859	.170 (.160 - .180)	.074
2 Factor	WLSMV	449.008/64	.921	.904	.140 (.130 - .150)	.061
3 Factor	WLSMV	420.983/62	.926	.907	.138 (.120 - .150)	.059
Rule of thumb for acceptable model (Hogg et al., 2023; Hu & Bentler, 1999)			≥.90	≥.90	≤.08	≤.08

Note: The MLR estimator treated the data as continuous; the WLSMV estimator treated the data as ordinal.

Table 7

Summary of the Model Fit Parameters with the WLSMV Estimator after Modification

Model	χ^2/df	CFI	TLI	RMSEA (90% CI)	SRMR
3-Factor[1]	346.252/62	.942	.927	.122 (.110 - .135)	.053
3-Factor[1,2]	234.193/62	.965	.956	.950 (.082 - .108)	.042
2-Factor[2]	350.462/64	.941	.928	.121 (.109 - .133)	.051
2-Factor[3]	231.978/61	.965	.955	.096 (.083 - .109)	.046
2-Factor[2,3]	173.191/61	.977	.971	.078 (.064 - .091)	.037
Rule of thumb for acceptable model (Hogg et al., 2023; Hu & Bentler, 1999)		≥.90	≥.90	≤.08	≤.08

Notes: 1) CEI1 and CEI2 on F3; 2) FI5 on CEI; 3) residual correlation (CEI1 & CEI2, FI3 & FI4, CEI5 & CEI6) based on M.I. 2-factor with WLSMV estimator.

The modification for the 2-factor structure was conducted gradually. After the change in the F15 position, the authors first specified residual correlation of items CEI1 and CEI2 (M.I. = 114.7). Second, the authors specified residual correlation between items FI3 and FI4 (M.I. = 38.3), and CEI5 and CEI6 (M.I. = 37.8). Subsequently, all the M.I. was were found to be below 20. FI5 was originally loaded onto factor FI, but according to EFA, the authors modified CFA, with FI5 loaded onto factor CEI. Moreover, based on the modification indices, CEI1 and CEI 2, which according to EFA would load on the 3- factor, were modified in the CFA by added adding residual correlation. The residual correlation between items was also specified for items FI3 and FI4, and CEI5 and CEI6.

Since the results of the original 2- and 3- factor models with specifications based on previous studies were similar (with little difference between each parameter), authors focused more on the 2-factor and modified 2-factor model. This was because the 2-factor model was the initial construct validation in the measurement development (Clayton & Karazsia, 2020). As can be seen in Figures 3 and 4, all the standardized factor loadings for each item were above .5. The correlation coefficient for the original 2-factor model was .791 and for the modified 2-factor model it was .798.

Figure 3

CFA Diagram of Original 2-Factor CAS Model

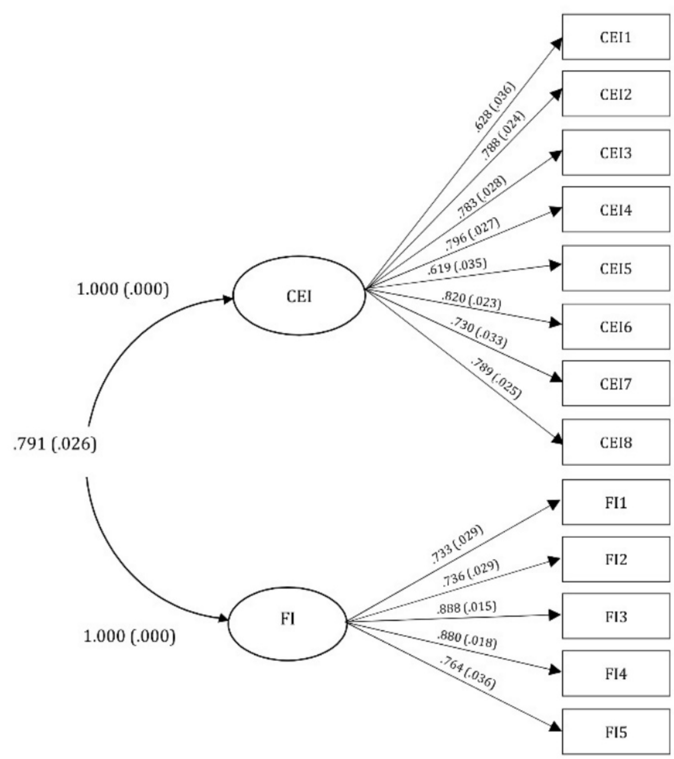
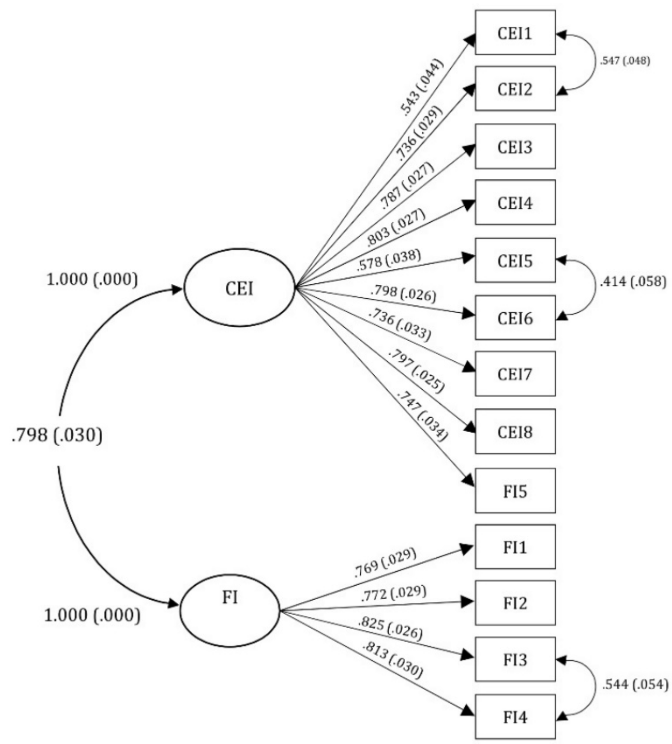


Figure 4

CFA Diagram of Modified 2-Factor CAS Model



Discussion

The measurement showed satisfactory reliability. Furthermore, the emerging factors from EFA in the sample showed that most items behaved in a similar fashion to the original model (F1 as cognitive-emotional impairment and F2 as functional impairment), apart from item FI5. Authors explored the 2- and 3-factor models, and differences were shown in items CEI1 and CEI2, which loaded to a new factor (F3). The new factor only consisted of two items, which indicates over-factoring, and compared to the 2-factor model, it was not parsimonious. Hence, the authors focused more on the 2-factor model.

The authors conducted confirmatory factor analysis based on the original 2-factor model (cognitive-emotional impairment and functional impairment) in line with the study of Clayton and Karazsia (2020). This model was found to be the best fit to the data in the case of French samples (Mouguiama-Daouda et al., 2022); Philippine samples (Simon et al., 2022); and Korean samples (Jang et al., 2023). The authors considered the original 2-factor model to be the best fit among the originally explored models in the Indonesian samples, similar to the Australian and New Zealand samples. Although the findings did not support the validity of the scale, the 2-factor model was clearly a better fit for the data (Feather & Williams, 2022).

Authors also considered a 1-factor model, which Wullenkord et al. (2021) reported to be a better model than the original 2-factor one, although their findings did not support the validity of the scale on their German sample. It was also claimed to be better than the 3-factor model (intrusive symptoms CEI1-CEI4, reflections on CA CEI5-CEI8, and functional impairment FI1-FI5) proposed by Larionow et al. (2022), which purported to be theoretically more consistent with the content of the CAS statements and had better fit indices than the original 2-factor solution, although both models had a good fit to a Polish data sample.

The authors investigated alternative models from different estimators (MLR and WLSMV); alternative models from previous studies (1-, 2- and 3-factor models), and also alternative models based on modification indices. The results of the original model from CFA did not support the validity of the scale in the Indonesian sample. The authors evaluated the model fit based on the rules of thumb from experts, which consist of global and local fits.

The global fit (exact fit) was the Chi-square. The local fit measures (also known as incremental fit indices), an assessment of how well a model approximates to the observed data compared to the rules of thumb of the fixed threshold according to experts, produced varied results. Authors used the rules of thumb of Hu and Bentler (1999) and Hogg et al. (2023). For consideration of results, Kline (2023) clarified that Hu and Bentler never intended their fixed thresholds for the RMSEA, CFI, SRMR, and other approximate fit indexes, to be treated as anything other than rules of thumb in their study.

The result of the MLR estimator was presented because previous studies used it to validate the CAS construct. Model parameters are indeed usually estimated with the ML estimator with alternative of MLR, but while this eases the assumption of normality, it still requires data to be continuous, and thus its suitability for ordered rating scales producing distinct data remains debatable (Brauer et al., 2023). Li (2016) reported that WLSMV was less biased and more accurate than MLR in estimating factor loadings across nearly all conditions, but that it yielded moderate overestimation of the inter-factor correlation when the sample size was small or/and when the latent distributions were moderately nonnormal.

The result from the MLR estimator, although having a lower ratio between Chi-square and degree of freedom, and RMSEA compared to the WLSMV estimator, still showed an unacceptable model fit. Furthermore, the result of each estimator in this study showed that both Chi-square and RMSEA failed to meet the rules of thumb, while the SRMR of each estimator all passed. Meanwhile, the WLSMV estimator showed slightly better results in the 2- and 3-factor models, especially in the parameters of CFI and TLI (higher than .90).

The authors considered the original 2-factor model as the best fit among the originally explored model (from the past studies), since the authors considered the parsimony and as there was little difference with the 3-factor model. But, since the model continued not to fit data, the authors made modifications based on the modification indices from the 2-factor model with the WLSMV estimators.

Based on the modifications, the model that fit data based on the rules of thumb was a 2-factor model with its specifications. The authors moved the position of F15 and the specified residual correlation between three pairs of items. Correlated errors may arise, for example, from items that are very similarly worded, reverse-worded, or differentially prone to social desirability (Brown, 2015).

Items CEI1 and CEI2, FI3 and FI4, and CEI5 and CEI6 might have similarly worded, context, and result in similar perceptions. Items CEI1 and CEI2 have similar phrasing and wording, with only the last part being different. Moreover, the final words of these two items tend to be perceived in a similar way, as having difficulty sleeping might cause a person to have difficulty concentrating, or vice versa. Items FI3 and FI4 are contained a person's functional impairment in the context of ability and performance, while items CEI5 and CEI6 might be perceived to be similar in terms of hopelessness causing anxiety.

The authors also specified FI5 to load on CEI based on the EFA result, where its factor loadings were salient in F1 (CEI). In this study, FI5 seems to be closer to CEI than to its originally hypothetical construct, FI. There may be several reasons for this result. The phrasing of item FI15 "My friends say I think about climate change too much," contains the word 'think', which has a tendency to be perceived as a cognitive impairment rather than a functional impairment in the Indonesian context. The differences between the original and authors' modified model might also be a result of the sample, for which the authors specified an age criterion, and there may also be cultural aspects that influence the responses to the item. Collectivist and individualist cultures can lead to different thought processes, which can lead to different patterns of people's perceptions. Consequently, different model specifications compared to the original may be produced.

This study is the first empirical psychological study to investigate climate anxiety in an Indonesian sample, and to treat the data as ordinal. Following this research, it is expected that further similar psychometric testing of the Climate Anxiety Scale will be conducted. As Price et al. (2015), state the assessment of reliability and validity is an ongoing process with different patterns of results across multiple studies. The authors hope that result findings will enrich CAS measurement validation.

In this research, four important limitations should be noted. First, the study focused only on young people, so it may not reflect other population groups. Future research could expand the scope of the participant criteria. Second, in the procedure undertaken, recruiting respondents might have resulted in unbalanced gender proportions. Third, this study did not accommodate evidence for the absence of social desirability in the responses. Fourth, although the authors explained the modified indices of the 2-factor model with caution, there was no strong theoretical reasoning, so the authors hope this did not result in misleading findings.

These issues can be addressed in subsequent studies, which should include other measurements for criterion validity; other methods apart from self-report measures for validation; a more balanced set of sample characteristics; inclusion of social desirability item identification; and consideration of alternative approaches, such as item response theory (IRT), to provide evidence for validity.

Conclusion

This study is the first to investigate climate anxiety in an Indonesian sample and to treat the data as ordinal. Based on research findings, the authors found no satisfactory validity of the climate change anxiety scale in the Indonesian population. Nonetheless, the 2-factor model was clearly a better fit for the data. CAS met satisfactory reliability, and although most items behaved similarly to the original 2-factor structure (apart from F15) based on EFA, they did not show a reasonable fit based on CFA. Therefore, the authors carefully made modifications based on the modified indices of the 2-factor structure and to meet a reasonable local fit measurement. It was not the authors' intention to propose a different factor structure. Consequently, given that the authors could not satisfactorily replicate the original 2-factor CAS structure, the authors recommend a combination of other measurements, methods, and approaches to gain more comprehensive CAS validity findings. The authors hope the findings from this study will provide the basis for other researchers to investigate climate anxiety further. In addition, the authors hope it will provide more understanding and the contribution of productive approaches to working with anxiety in a world facing a climate crisis, with the need for psychology-ecological transformation to ensure sustainable living.[]

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Author Contribution Statement

Siti Jaro'ah: Conceptualization; Data Curation; Funding Acquisition; Investigation; Methodology; Project Administration; Resources; Validation; Visualization; Writing Original Draft; Writing, Review & Editing. **Kuni Saffana:** Data Curation; Formal Analysis; Funding Acquisition; Investigation; Methodology; Resources; Validation; Visualization; Writing Original Draft; Writing, Review & Editing.

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