Learning and Individual Differences 41 (2015) 14–20

Contents lists available at ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

Using factor mixture modeling to identify dimensions of cognitive test anxiety

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ARTICLE INFO

Article history:
Received 3 September 2014
Received in revised form 24 April 2015
Accepted 16 June 2015
Available online xxxx

Keywords:
Test anxiety
Latent class analysis
Factor mixture model
Multidimensional measure

ABSTRACT

The research on test anxiety has repeatedly attempted to provide a more refined measurement of multiple dimensions of the construct. Divergence in the field has repeatedly arisen in the specific dimensions, but there is a broad acceptance that there are various manifestations of test anxiety. The current study attempts to specifically explore the potential for identifying subcomponents of the construct referred to as cognitive test anxiety. The analyses did not support the initial prediction that a temporal determination of factors (i.e., related to the Learning-Testing Cycle) would arise. Alternatively, exploratory factor mixture modeling (EFMM) demonstrated that there were two latent classes of students (based on levels of reported test anxiety). Furthermore, the EFMM demonstrated that the factorial structure of cognitive test anxiety differed between these two latent classes. Specifically, undergraduate students with low levels of cognitive test anxiety represented cognitive test anxiety as a unidimensional construct. However, for those students with high levels of test anxiety, there were two distinct factors. The results suggest that those learners with high-test anxiety are able to differentiate among more different "types" of test anxiety as compared to their non-anxious peers.

1. Introduction

Research in test anxiety has become progressively refined over the past 50 years, with greater precision in identifying subcomponent aspects of anxious responses to evaluative events since Liebert and Morris (1967) identified emotionality and worry as primary factors for test anxiety. Research over this time frame has consistently identified behavioral and attitudinal tendencies for individuals with high levels of test anxiety in these two broad domains. Indicators of high levels of emotionality generally include specific physiological indicators such as perspiration, headaches, elevated heart rate, tension, and cortisol production (Daly, Chamberlain, & Spalding, 2010; Mattarella-Micke, Mateo, Kozak, Foster, & Beilock, 2011; Sarason, 1984). Alternatively, high levels of the classic worry factor – which is also referred to as cognitive test anxiety (e.g., Cassady, 2010; Lowe et al., 2008) – is associated with a broader range of behaviors and beliefs that impact the learning and testing experiences for students. Commonly identified characteristics associated with this dimension of test anxiety include (a) heightened perceived threat for tests; (b) inferior cognitive processing, organization skills, and study strategies; (c) susceptibility to cognitive interference (i.e., distractibility) during both study sessions and the exam period; and (d) motivational perspectives that promote task avoidance, failure acceptance, and disengaged coping strategies (e.g., Cassady, 2004a, 2010; Cassady & Johnson, 2002; Davis, Distefano, & Schutz, 2008; Sarason, 1984; Schwarzer & Jerusalem, 1992; Zeidner, & Matthews, 2005).

Dominant models of test anxiety assert that both domains are relevant in explaining the learning and testing experiences for individuals with high-test anxiety, with the emotionality factor serving largely as a cue to the learner regarding the level of threat imposed by an evaluative condition (Hembree, 1988; Mattarella-Micke et al., 2011; Spielberger & Vagg, 1995; Zeidner & Matthews, 2005). When this threat appraisal is identified, the cognitive test anxiety beliefs and behaviors become prevalent and influence learning and performance (e.g., Cassady, 2004a; Hembree, 1988). Given the widespread acceptance of the physiological indicators of emotionality and the research identifying that cognitive test anxiety is more directly linked to test performance levels, the cognitive component has received more attention in the literature focused on the structure and measurement of test anxiety (e.g., Cassady & Finch, 2014; Lowe et al., 2008; von der Embse, Kilgus, Segool, & Putwain, 2013). As such, our investigation focuses on the cognitive dimension of test anxiety, specifically exploring the potential for multiple dimensions of cognitive test anxiety as measured through a widely used self-report measure.

1.1. Theoretical multidimensionality of cognitive test anxiety

As early as the 1980's, there was attention given to further differentiating test anxiety beyond the initial worry and emotionality factors. The most popular measure in this line was Sarason's (1984) Reactions

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http://dx.doi.org/10.1016/j.lindif.2015.06.002
1041-6080/

to Tests scale that identified worry and test-irrelevant thinking as distinct elements representing the cognitive dimensions of test anxiety. While there is no universal acceptance of specific factors within the cognitive domain of test anxiety, the research started at that time sparked a series of engaging studies into the diverse experiences test anxious learners encounter in evaluative settings. The results demonstrated that there were a wide range of beliefs and behaviors that are commonly reported by individuals with test anxiety.

One approach to attempting to differentiate among these various beliefs and behaviors has been to examine "types" or "profiles" of test anxiety. Zeidner and Matthews (2005); see also Zeidner, 1998) summarized the dominant types that had been proposed in the literature, proposing six types of test anxiety: (a) study skills deficits, (b) anxiety blockage and retrieval failure, (c) failure acceptance, (d) failure-avoidance, (e) self-handicapping, and (f) perfectionism. Zeidner's summarization of these types of anxiety can be largely seen as an integration of Covington's (1992) self-worth theory with two classic explanations for the influence of cognitive test anxiety on performance–anxiety blockage and skills deficits.

An additional approach to examining differences in cognitive test anxiety recognizes variations in the manifestation of test anxiety across three phases of the "learning-testing cycle". This model proposes that test anxious learners demonstrate different beliefs and behaviors related to evaluative pressure during the test preparation, test performance, and test reflection phases (Raffety, Smith & Ptacek, 1997; Schwarzer & Jerusalem, 1992). Both of these procedures for distinguishing among test anxiety experiences (as well as others) have merit and critical evaluation of these dimensional approaches lies beyond the current focus of this study. However, the viability of all these models center on the recognition that there are variations among test anxious learners' experiences in evaluative settings. That is, learners who are identified as high-test anxious are not a homogenous group — and the beliefs and behaviors an individual with test anxiety exhibits may change as situational factors (e.g., perceived difficulty, proximity to testing) are modified.

The "anxiety blockage" view of test anxiety is perhaps the most prototypical and classic view. This classic explanation proposes that test anxiety negatively impacts performance due to cognitive interference and distraction experienced during the testing session (e.g., self-deprecating ruminations, test-irrelevant thinking, cue overload during retrieval; Deffenbacher, 1980; Geen, 1980; Sarason, 1984). More recent explanations for this effect highlight the importance of recognizing cognitive interference also occurs during the test preparation phase, when learners attempt to encode content to be recalled during the test performance phase (Cassady, 2010). Empirical research on this effect – which includes work on "choking under pressure" – has confirmed high-anxiety learners are more susceptible to performing at a lower level of proficiency when they perceive evaluative stress (Beilock, 2010; DeCaro, Thomas, Albert, & Beilock, 2011; Covington & Omelich, 1987; Mattarella-Micke et al., 2011). Chen and Chang (2009) reframed this classic representation of test anxiety using cognitive load theory, reporting that students with high-test anxiety experience a greater cognitive load in evaluative settings (including test preparation), with extraneous load demands drawing necessary cognitive resources from the task at hand.

However, this view of test anxiety has been contested, driven in part by research that demonstrates high overlaps in state anxiety and cognitive abilities (e.g., Sommer & Arendasy, 2014). This approach to viewing test anxiety through a skills deficit model is supported by research demonstrating that test performance decrements for test anxious learners are generally not relieved in non-evaluative stress contexts (e.g., Cassady, 2004b), and verbal working memory capacity for high test-anxious learners does not vary between high and low evaluation threat settings (Putwain, Shah, & Lewis, 2014). In line with these findings, the second broad explanation for cognitive test anxiety builds from research demonstrating that learners with test anxiety display deficiencies in cognitive operations and activities (i.e., self-regulated learning strategies) — regardless of evaluative stress (e.g., Naveh-Benjamin, 1991). This view of test anxiety holds that students with test anxiety experience poor test performance due to the inability to effectively encode, organize, or comprehend content to be used during the test session. This view has been validated by work with subjects who attempt to organize to-be-learned content in a non-evaluative setting (Naveh-Benjamin) as well as those who take practice tests that have no evaluative pressure (i.e., in a lab setting, Cassady, 2004b; Putwain et al., 2014). The overarching view in this view of test anxiety is that the evaluative event itself does not impose a stressor that "blocks" retrieval of established knowledge for test anxious learners — rather the deficit comes from limitations in working memory, executive functioning, or self-regulation that preclude effective encoding (Owens, Stevenson, Norgate, & Hadwin, 2008).

1.2. Applied multidimensional model of cognitive test anxiety

While there has been clear evidence validating the presence of both skills deficit and anxiety blockage (or cognitive interference) "forms" of cognitive test anxiety, the standard strategies of assessment of cognitive test anxiety generally do not provide information regarding learner differences on the various dimensions of cognitive test anxiety that may influence student experiences. While some measures identify the different broad themes of test anxiety captured by these perspectives, in general the measurement models for test anxiety scales result in a single scale score for cognitive test anxiety (or worry). However, as Serrano-Pintado and Escolar-Llamazares (2014) recently argued, identifying differential profiles of test anxiety are essential to support effective treatment strategies. In their study, contrasting students with "rational anxiety" (students with poor coping and study skills who worry about tests) and "irrational anxiety" (students with good coping and study skills who *still* worry about tests) revealed that information about the "type" of anxiety can help isolate the most effective intervention strategies to support success (i.e., study skills interventions were only effective for those with "rational" anxiety).

The advancement we believe that was provided in Serrano Pintado and Escolar Llamazares' (2014) approach to the treatment of test anxiety was afforded by using more individually-specific information when determining optimal test anxiety interventions. In early work focused on primarily unidimensional treatment strategies (i.e., skills training vs relaxation), results were generally underwhelming and showed limited success overall as applied to a general student population (Hembree, 1988). However, reviews of more contemporary intervention efforts have demonstrated promising results for test anxiety intervention strategies, particularly when the interventions employed combinatory intervention techniques (e.g., cognitive–behavioral approaches, skills training plus relaxation). Research attempting to organize and summarize the findings across the literature has suggesting five general categories of test anxiety interventions (behavioral, cognitive, cognitive–behavioral, study skills, and test-taking skills; e.g., Ergene, 2003; von der Embse, Barterian, & Segool, 2013). We believe that work in the measurement of test anxiety can support this positive trend toward intervention utility by helping practitioners more effectively parse the population of test anxious learners to identify the underlying "form" or "type" of test anxiety and subsequently provide more targeted prescribed interventions. Identification of the specific needs learners have related to test anxiety, test preparation, and test performance can help isolate the intervention or interventions that are most likely to support each individual's success, and ideally lead to more efficient treatment implementation (Serrano-Pintado & Escolar-Llamazares, 2014).

1.3. Present investigation

The purpose of this study was to explore the potential of detecting differential representations of cognitive test anxiety among learners using a traditional self-report measure of cognitive test anxiety. Despite initial intention to capture multiple aspects of cognitive test anxiety, prior work with the scale used in this study has repeatedly demonstrated a predominantly unidimensional structure for cognitive test anxiety (Cassady & Finch, 2014; Furlan, Cassady, & Perez, 2009). Review of the items in the scale reveal that multiple perspectives to test anxiety are represented (e.g., anxiety blockage, skills deficits, learning–testing phase differences), but factor analyses conducted with university students have not demonstrated those subfactors of cognitive test anxiety. However, review of work such as Serrano-Pintado and Escolar-Llamazares (2014) that split the high anxiety group into types before examining program efficacy as well as recent studies using cluster methods and latent class analyses to identify "types" of test anxious learners (e.g., von der Embse et al., 2014) suggested a different method may more effectively address the viability of a multidimensional representation of cognitive test anxiety.

Specifically, the goal of the study was to identify through factor mixture modeling (see Lubke & Muthén, 2005) if there were different "classes" represented in the undergraduate student population — and within those classes if the factor structure of cognitive test anxiety was similar or different. The rationale for this approach comes from the realization that students with low levels of test anxiety may hold different conceptualizations for the construct than those with heightened levels of anxiety. Simple factor analytic studies lump all learners into one class and identify the structure of the scale based on that presumed homogenous group.

In essence, our study has been undertaken to examine response patterns for undergraduate learners to simultaneously identify if the factorial conceptualization for cognitive test anxiety is consistent across all students, or if subgroups of students are represented and the factor structure differs as a function of their group membership. For example, it is possible that students with high and low levels of anxiety may perceive different dimensions of the test anxiety construct?

2. Method

2.1. Participants

Data were collected over the course of two years at a Midwestern United States university. Participants in this sample were collected from a standard university research participation pool drawing upon an undergraduate student population enrolled primarily in educational psychology courses ($N = 619$). The students provided informed consent at the time of the study and completed the survey as one of several options to fulfill a course credit requirement. Of those participants reporting, the sample demographics reflected 64% female and 91% Caucasian, with a mean age of 22. The participants represented the population in the research pool from which they were drawn.

2.2. Measure

The Cognitive Test Anxiety Scale (CTAS) was an instrument created to measure this cognitive component of test anxiety in learners (Cassady & Johnson, 2002). Extending the original anxiety blockage orientations of test anxiety, this assessment examined the learner's experience across the entire learning–testing cycle (Cassady, 2004b), acknowledging that test anxiety also impacts test preparation and test reflection (e.g., Covington & Omelich, 1987; Schwarzer & Jerusalem, 1992). The CTAS has been validated and used as a self-report instrument in various settings, including the US (e.g., Cassady, 2004a, 2004b; Cassady & Johnson, 2002; Ramirez & Beilock, 2011), Great Britain (Daly, Chamberlain, & Spalding, 2010; Kapetanaki, 2010), and Greece (Tsianos, Lekkas, Germankos, Mourlas & Samaras, 2009). Translation of the scale into Chinese (Chen, 2007; Zheng, 2010), Arabic for use in Kuwait (Cassady, Mohammed, & Mathieu, 2004), and Spanish for native Argentinians (Furlan et al., 2009) demonstrated that the scale was also valid across cultural contexts and useful for examining cross-cultural patterns of test anxiety. However, subsequent analyses of the original CTAS demonstrated that the use of reverse-coding on the original scale actually produced two factors: Cognitive Test Anxiety and Test Confidence. Cassady and Finch (2014) demonstrated that a reduced length version of the CTAS (17-items) that was created by removal of reverse-coded items provided a conceptually preferable and more parsimonious measure of cognitive test anxiety than either the original single factor full-length version or the two-factor solution using all the original items.

The measure used in this study was the Cognitive Test Anxiety Scale Revised (CTAR), which included the 17 items from the reduced length CTAS and 8 additional items explicitly focused on promoting more indicators of test anxiety experiences in all three phases of the Learning–Testing Cycle. The additional items were generated through collaborative discussions with researchers using the CTAS, attempting to provide more conceptual indicators of the cognitive test anxiety experience across the Learning-Testing Cycle, based on both theory and discussion with students experiencing test anxiety.

2.3. Procedure

Students completed the CTAR in one of two ways, either through online survey response or in small groups with a survey administrator in standard university classrooms. Each participant provided informed consent, completed a short demographic questionnaire, then submitted their responses to the 25-item CTAR along with three other surveys unrelated to this project (CTAR was completed first in both settings). The participant responses to the CTAR are completed with a 4-point Likert-type response that includes the following response options: 1 — "Not at all typical of me"; 2 — "Somewhat typical of me"; 3 — "Quite typical of me"; 4 — "Very typical of me"). These response options are the same as the original CTAS, and follow the response categories for other traditional measures of test anxiety surveys (Sarason, 1984). The items appear in Table 1. Data from the students' responses during small group administration were subsequently entered into the database captured from online surveys for analyses, with validity checks for the data entry to ensure that no errors in transfer of data were made. Students who left individual items blank in both data collection conditions were removed from the current analysis. Comparison of student responses (both missing data and item response patterns) demonstrated no differences between method of data collection (online vs. in-person), therefore we combined all students from both forms of data collection into one set for subsequent analyses.

2.4. Data analysis

In order to examine the latent structure of the CTAR, both with respect to the potential multidimensional nature of test anxiety, and in regards to the potential for test anxiety to manifest in fundamentally different ways for underlying latent groups of individuals in the population, an exploratory factor mixture model (FMM) was fit to the data using version 7 of Mplus, which employs full-information maximum likelihood to account for missing data (Muthén & Muthén, 2012). FMM is a mixture modeling framework that simultaneously identifies the latent structure underlying a set of indicator variables (e.g. items on the CTAR) using exploratory factor analysis, as well as the latent structure underlying a group of individuals much as would be true with latent class analysis (McLachlan & Peel, 2000). FMM can be framed as either exploratory or confirmatory in nature, just as can factor analysis and latent class analysis. For the current study, exploratory FMM was used because prior research has not provided clear direction regarding the number or nature of latent factors that may underly the new version of the CTAR, nor have latent classes with respect to cognitive test anxiety been identified with any of the precursor measures. Thus, a primary goal of this work was to explore both aspects of test anxiety (latent classes and factors) simultaneously, and thereby

Table 1
Geomin rotated factor loadings of CTAR item responses for latent classes 1 and 2.

Item	Latent Class 1 (n = 249)		Latent Class 2 (n = 370)	
	F1	F2	F 1	F 2
1. I lose sleep over worrying about examinations.*	0.259	**0.607**	**0.594**	−0.205
2. I worry more about doing well on tests than I should.*	0.005	**0.784**	**0.559**	−0.271
3. I get distracted from studying for tests by thoughts of failing	**0.741**	0.203	**0.626**	−0.019
4. I have difficulty remembering what I studied for tests	**0.802**	0.017	**0.360**	**0.399**
5. While preparing for a test, I often think that I am likely to fail.	**0.877**	−0.008	**0.534**	0.083
6. I am not good at taking tests.*	**0.797**	0.024	0.008	**0.793**
7. When I first get my copy of a test, it takes me a while to calm down to the point where I can begin to think straight.*	**0.868**	0.008	**0.619**	0.013
8. At the beginning of a test, I am so nervous that I often can't think straight.*	**0.877**	0.017	**0.659**	0.078
9. When I take a test that is difficult, I feel defeated before I even start.*	**0.917**	−0.113	**0.572**	0.125
10. While taking an important examination, I find myself wondering whether the other students are doing better than I am.*	**0.787**	−0.082	**0.472**	−0.082
11. I tend to freeze up on things like intelligence tests and final exams.*	**0.880**	−0.010	**0.416**	**0.402**
12. During tests, I find myself thinking of the consequences of failing.*	**0.843**	0.037	**0.653**	−0.045
13. When I take a test, my nervousness causes me to make careless errors.*	**0.785**	0.187	**0.593**	0.083
14. My mind goes blank when I am pressured for an answer on a test.*	**0.788**	0.076	**0.555**	0.272
15. During tests, the thought frequently occurs to me that I may not be too bright.*	**0.922**	−0.085	**0.567**	0.145
16. During a course examination, I get so nervous that I forget facts I really know.*	**0.849**	0.086	**0.499**	**0.353**
17. I do not perform well on tests.*	**0.920**	−0.077	−0.031	**0.912**
18. During tests, I have the feeling that I am not doing well.*	**0.821**	0.080	**0.310**	0.298
19. I am a poor test taker in the sense that my performance on a test does not show how much I really know about a topic.*	**0.723**	0.047	0.044	**0.728**
20. After taking a test, I feel I should have done better than I actually did.*	**0.732**	0.001	**0.326**	0.274
21. My test performances make me believe that I am not a good student.	**0.952**	−0.097	0.176	**0.299**
22. I often realize mistakes I made right after turning in a test.	**0.649**	0.163	**0.543**	−0.231
23. When I finish a hard test, I am afraid to see the score.	**0.730**	0.084	**0.550**	−0.103
24. When I get a good grade on a test, it is usually because I got lucky.	**0.978**	−0.206	0.252	0.219
25. I don't seem to have much control over my test scores.	**1.005**	−0.172	0.219	**0.422**

Note. * — Item was on the original CTAS. Items loading on factors indicated in bold.

begin the development of a unified framework for understanding how it might be manifest in the population.

FMM yields a solution involving both the optimal number of factors underlying the observed indicators and the optimal number of latent classes underlying the individuals. In this study exploratory FMM (EFMM) was used to identify a potentially optimal combination of factor and latent class structure in the data. As outlined by Lubke and Muthén (2005), the EFMM is appropriate for situations in which hypotheses regarding both the factor structure (i.e. measurement model) and the latent class structure are not fully defined a priori. Muthén (2008) also describes the use of EFMM in the case where neither the number of factors nor the number of latent classes is known prior to data collection. McLachlan, Do, and Ambroise (2004) provide an excellent example of application of EFMM in practice in just such a situation. In the context of EFMM, factor model structure is treated as separate for each latent class, and a series of models are fit to the data, differing in terms of the number of factors and the number of latent classes (McLachlan & Peel, 2000; Dolan & van der Maas, 1998). In order to ascertain which is optimal, goodness of fit statistics are used, including the Akaike Information Criterion (AIC; Akaike, 1978), the Bayesian Information Criterion (BIC; Schwarz, 1978), and the sample size adjusted BIC (aBIC; Sclove, 1987). Each of these statistics is based on a measure of variance in the indicators unexplained by the model, with penalties for model complexity. Prior research has shown each of the three to provide accurate indications of optimal model fit in many situations, with the aBIC demonstrating particularly good performance in many cases (Enders & Tofighi, 2008). Given recommendations for FMM (McLachlan & Peel), we referred to each of these statistics in identifying the optimal model. In addition, the substantive nature of the models was also taken into consideration when deciding on the best fitting model. In other words, the model selected as best needed not only to provide the best fit statistically, but also had to be sensible in terms of the item response patterns of the individuals contained within each latent class, and in terms of how the items loaded with the various factors. With regard to the exploratory factor analysis portion of the model, the Geomin rotation was used. Geomin, which is an oblique rotation allowing factors to be correlated, has been shown to perform well in a variety of data conditions, including when indicator variables were skewed and factor to item relationships were relatively weak (Finch, 2011; Sass & Schmitt, 2010). Finally, of the 619 individuals in the sample, 605 provided complete responses to all items, whereas 14 were missing at least 1 response, and no item had more than 2 missing values. Maximum likelihood estimation was used to obtain parameter estimates. In addition to being the generally recommended approach for estimation, it is also regarded as state of the art with respect to handling missing data (Enders, 2013), and served that purpose in the current study.

Table 2
Fit statistics for EFMM.

Model	AIC	BIC	aBIC
2 classes 1 factor	34,100.55	34,990.26	34,221.94
2 classes 2 factor	33,922.03	34,665.92	34,002.19
2 classes 3 factor	33,781.02	34,517.66	33,991.42
2 classes 1 factor	33,550.63	34,129.28	33,739.88
2 classes 2 factors	**32,286.31**	**33,752.01**	**32,701.14**
2 classes 3 factors	32,954.28	33,835.48	33,203.69
3 classes 1 factor	33,044.39	34,049.57	33,328.88
3 classes 2 factors	32,548.76	33,872.76	32,923.49
3 classes 3 factors	32,981.77	33,471.68	33,000.19
4 classes 1 factor	35,259.80	36,601.52	35,639.55
4 classes 2 factors	35,166.42	35,891.06	35,541.72
4 classes 3 factors	35,405.08	36,007.99	35,732.00

3. Results

AIC, BIC, and aBIC values for the various FMM solutions that were fit to the data appear in Table 2. In total, models ranging from 1 to 3 factors and 1 to 4 latent classes were examined and compared using the information indices. An attempt was made to fit larger models, but these would not converge. Smaller values of the information indices indicate superior model fit, so that based on these results, the 2 class, 2 factor model provided the best statistical fit to the data. Its values appear in bold in Table 2.

Table 1 contains the Geomin rotated pattern coefficients for the individual CTAR items for each latent class identified by the FMM. Items were deemed to be associated with a factor if the pattern coefficient value was 0.3 or greater (Tabachnick & Fidell, 2013). Based on these results, it appears that for latent class 1 (LC1) all CTAR items, except for 1 and 2, clearly loaded with the first factor. The two items that do not load with this factor were "I lose sleep over worrying about examinations" and "I worry more about doing well on tests than I should". Furthermore, for LC1 the pattern coefficients were all in excess of 0.6, with most greater than 0.7, indicating very strong relationships between the items and the factors.

In contrast to the essentially single factor solution for LC1, for latent class 2 (LC2) the items loaded onto two distinct factors. Sixteen items were associated with factor 1; the content of these items were primarily oriented on aspects of cognitive interference during both test preparation and test performance periods. For LC2, five items were loaded directly (see Table 1) which address appraisals of test taking ability and test performance potential. In addition, three items that address both of these factors implicitly by identifying exam performance failures due to specific cognitive failures were cross-loaded between the two factors for LC2. Finally, one item (CTAR24, which focused on attributing exam success to "luck") did not load onto either factor. The correlations between the two factors was 0.38 for LC1 and 0.51 for LC2. Given the very different structure of the factors for the two latent classes, it is not advisable to make direct comparisons of these differing correlations across the groups. However, it does appear that the relationship between the latent traits in LC2 was relatively large, reflecting the fact that there was some factor overlap for this group. On the other hand, the correlation for LC1 was more moderate in magnitude, indicating less overlap between the factors for that group.

Table 3 includes the latent class means and standard deviations for the individual CTAR items, as well as for the total CTAR scale (created by summing the 25 items into a single score). Across the items in this sample the means for LC1 were lower than those for LC2. These results suggest that members of LC1 reported lower levels of anxiety with regard to the individual elements being assessed by the items than did those in LC2. In addition, based on the results of an independent samples t-test, the mean of the entire scale for LC1 was statistically significantly lower than the scale mean for LC2 ($t = 36.48$, $p < 0.001$).

Table 3
Means and standard deviations of CTAR item responses for latent classes 1 and 2.

Item	Latent class 1 (n = 249)		Latent class 2 (n = 370)	
	M	SD	M	SD
I lose sleep over worrying about examinations.*	1.934	0.667	2.673[a]	0.853
I worry more about doing well on tests than I should.*	2.502	0.619	3.048[a]	0.876
I get distracted from studying for tests by thoughts of failing	1.648	0.544	2.893[a]	0.787
I have difficulty remembering what I studied for tests	1.861	0.588	3.126	0.752
While preparing for a test, I often think that I am likely to fail.	1.569	0.486	2.841[a]	0.814
I am not good at taking tests.*	2.011	0.591	3.338[b]	0.604
When I first get my copy of a test, it takes me a while to calm down to the point where I can begin to think straight.*	1.486	0.491	2.633[a]	0.780
At the beginning of a test, I am so nervous that I often can't think straight.*	1.393	0.469	2.634[a]	0.713
When I take a test that is difficult, I feel defeated before I even start.*	1.654	0.474	3.019[a]	0.765
While taking an important examination, I find myself wondering whether the other students are doing better than I am.*	1.934	0.650	2.816[a]	0.900
I tend to freeze up on things like intelligence tests and final exams.*	1.701	0.482	3.074	0.704
During tests, I find myself thinking of the consequences of failing.*	1.682	0.514	2.952[a]	0.776
When I take a test, my nervousness causes me to make careless errors.*	1.862	0.489	3.014	0.769
My mind goes blank when I am pressured for an answer on a test.*	1.896	0.574	3.190[a]	0.683
During tests, the thought frequently occurs to me that I may not be too bright.*	1.275	0.449	2.625[a]	0.758
During a course examination, I get so nervous that I forget facts I really know.*	1.645	0.465	3.084	0.667
I do not perform well on tests.*	1.650	0.448	3.021[b]	0.443
During tests, I have the feeling that I am not doing well.*	1.877	0.521	2.959[a]	0.850
I am a poor test taker in the sense that my performance on a test does not show how much I really know about a topic.*	2.014	0.671	3.233[b]	0.659
After taking a test, I feel I should have done better than I actually did.*	2.261	0.681	3.253[a]	0.854
My test performances make me believe that I am not a good student.	1.520	0.392	2.738[b]	0.909
I often realize mistakes I made right after turning in a test.	2.270	0.687	3.097[a]	0.882
When I finish a hard test, I am afraid to see the score.	2.298	0.643	3.459[a]	0.862
When I get a good grade on a test, it is usually because I got lucky.	1.375	0.391	2.349	0.913
I don't seem to have much control over my test scores.	1.260	0.302	2.438[b]	0.825
CTAR total	44.52	8.48	73.71	10.34

Note. * — Item was on the original CTAS.
[a] Factor 1 for LC2.
[b] Factor 2 for LC2.

Cohen's *d* effect size was calculated to provide context regarding the magnitude of this difference. The value in this case was 3.09, indicating a large difference between the groups' means (Cohen, 1988). In other words, individuals in LC1 had significantly lower overall test anxiety, as measured by the total CTAR score, than did those in LC2. Finally, in an attempt to further understand the nature of the two latent classes, their gender and ethnicity distributions were compared, using logistic regression. For this analysis, the dependent variable was LC, and the independent variables were sex and ethnicity, where the latter variable was coded as 1 (Caucasian) or 0 (other). Neither independent variable was statistically significantly related to LC membership ($\alpha = 0.05$). In terms of relative frequencies within the sample, the two latent classes had nearly identical proportions of females, with 64.0% for LC1 and 64.0% for LC2. Similar results were found for ethnicity as well, with LC1 being 91.8% Caucasian, and LC2 being 92.7% Caucasian. Thus, the latent classes could not be differentiated by their gender or ethnic makeup.

4. Discussion

This study provides a novel perspective on research attempting to identify the structure of a multidimensional representation for cognitive test anxiety. The study was initially undertaken based on the hypothesis that there may be “types” of test anxious learners that can be identified through distinctions among the phases of the Learning–Testing Cycle (e.g., Schwarzer & Jerusalem, 1992) or between “skills” and “blockage” indicators of test anxiety (e.g., Sommer & Arendasy, 2014). However, the results did not follow that initial expectation. While the results did not support our initial expectations, they do provide guidance to the field regarding the measurement of cognitive test anxiety (and presumably all forms of academic anxieties).

Specifically, our analyses demonstrated that students with low levels of cognitive test anxiety (Latent Class 1) recognize a unidimensional construct composed of most items on the CTAR. Conversely, those students with higher levels of cognitive test anxiety appear to identify two distinct aspects to cognitive test anxiety. The first is most consistent with symptoms consistent with cognitive interference for those with anxiety (e.g., distraction, worry, interfering thoughts; Cassady, 2010; Beilock, 2010; Sarason, 1984). However, as contrasted with traditional views that examine anxiety blockage only *during* the exam (e.g., Covington & Omelich, 1987; Deffenbacher, 1980), these items indicate anxiety blockage – or cognitive interference – can occur during both the test preparation and test performance phases (Raffety et al., 1997; Schwarzer & Jerusalem, 1992). The second factor identified by the high anxiety group focused on their perceived skill deficiencies in test taking (e.g., not good at taking tests, poor test taker; Matthews et al., 2006; Naveh-Benjamin, 1991; Zeidner & Matthews, 2005). Three items cross-loaded on both factors and warrant additional attention in future work, but initial review of the factor loadings and the item content appear to indicate that these items bridge the two primary orientations (e.g., freeze upon final exams, difficulty remembering what I studied).

There is a growing agreement that distinguishing among distinct aspects of test anxiety has both theoretical and practical value (e.g., Lowe, Grumbein & Raad, 2011; Lowe et al., 2008; Zeidner & Matthews, 2005). Simply, not all examinees face the same constellation of stressors when it comes to the issue of test anxiety, nor do those stressors impact performance equitably across individuals. Naturally, where this issue becomes most critical is in the attempts to alleviate the negative influences of test anxiety. Recent reviews of the intervention literature have demonstrated a variety of intervention strategies are generally effective in alleviating the experience of test anxiety in children, adolescents, and young adults (e.g., Cizek & Burg, 2006; Ergene, 2003; von der Embse, Barterian et al., 2013), but what remains elusive is pinpointing the intervention that will best serve each individual learner. The results of this study suggest that greater attention to factorial representations of test anxiety dimensions sensitive to those students with high levels of anxiety may provide greater precision in identifying specific challenges and potential solutions.

4.1. Limitations and directions for future research

The first primary limitation to the current study is based on the volunteer population from whom the data were collected. Future studies that can capture a broader representation of learners that has greater diversity in gender, race, and domains of academic interest would improve the generalizability of the findings. In addition, the inability to capture more detailed information on the participants regarding their financial status, parent educational background, age, and prior educational experiences (e.g., high school GPA) would strengthen the understanding of the overall construct. It would be desirable to also examine if the structure of cognitive test anxiety for high anxiety learners was similar in the adolescent population.

From a more direct theoretical perspective related to test anxiety, the use of only the CTAR in the current study limits the ability to effectively explore the full dimensionality of test anxiety for high and low anxious learners. We see great potential to the theoretical and practical branches in the field if measures of test anxiety that tap aspects other than just cognitive test anxiety were examined in a similar analytical fashion. Using a multiclass multifactor analytic strategies such as factor mixture modeling with a collection of scales that address proposed aspects in addition to the cognitive dimension, such as emotionality/physiological aspects, tension, or social derogation would augment the findings from the limited perspective afforded with this study (e.g., Friedman & Bendas-Jacob, 1997; Lowe et al., 2008; von der Embse, Kilgus et al., 2013). It is also possible that providing a broader battery of self-regulation and motivation instruments along with test anxiety may afford an empirical test of a typology for test anxiety suggested by Zeidner (1998). Continuing in that line, we foresee a wealth of theoretical and practical research that could test the effectiveness of assigning intervention strategies for high-test anxious learners that are highly specific to their individual needs.

With regard to the data analysis, a primary limitation of the method is the potential for making errors with respect to extracting the appropriate numbers of factors and latent classes (Lubke & Muthén, 2005). Given the complexity of the analysis, it is important to keep this issue in mind. For example, it is possible that a Type I error could be made in this circumstance, such that more factors and/or latent classes are extracted than are actually present in the data. Such an error would lead to the conclusion that there is more structure in the data than is actually present in the population. Relatively little empirical work has been done investigating the propensity of FMM to make such an error. Thus, readers should keep this issue in mind when interpreting the results. In addition, future research needs to be conducted to further verify the findings presented here, both in terms of the number of latent classes and the factor structure within each. Finally, researchers working in this area may also consider the possibility of using Exploratory Structural Equation Modeling, as it may provide greater flexibility with respect to modeling the item responses (Marsh, Morin, Parker, & Kaur, 2014). In particular, this approach might more easily allow the inclusion of latent variables reflective of the positive and negative wording of items, and the associated method effect inherent therein.

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