

## A Confirmatory Factor Analysis of the Structure of Abbreviated Math Anxiety Scale

Shahram vahedi Ph.D<sup>1</sup>  
Farahman Farrokhi Ph.D<sup>2</sup>

**1** Assistant professor of Educational Psychology, Faculty of Education and Psychology, University of Tabriz, Tabriz, Iran  
**2** Assistant Professor, English Department, The University of Tabriz, Iran

### Corresponding author:

Shahram Vahedi, Assistant professor of Educational Psychology, Faculty of Education and Psychology, University of Tabriz, 22 Bahman Ave., Tabriz, Iran.  
Tel: +98-411-3392090  
Email: vahedi117@yahoo.com

**Objective:** The aim of this study is to explore the confirmatory factor analysis results of the Persian adaptation of Abbreviated Math Anxiety Scale (AMAS), proposed by Hopko, Mahadevan, Bare & Hunt .

**Method:** The validity and reliability assessments of the scale were performed on 298 college students chosen randomly from Tabriz University in Iran. The confirmatory factor analysis (CFA) was carried out to determine the factor structures of the Persian version of AMAS .

**Results:** As expected, the two-factor solution provided a better fit to the data than a single factor. Moreover, multi-group analyses showed that this two-factor structure was invariant across sex. Hence, AMAS provides an equally valid measure for use among college students .

**Conclusions:** Brief AMAS demonstrates adequate reliability and validity. The AMAS scores can be used to compare symptoms of math anxiety between male and female students. The study both expands and adds support to the existing body of math anxiety literature.

**Keywords:** *Math anxiety, confirmatory factor analysis (factor analysis), factorial invariance*

*Iran J Psychiatry 2011; 6: 47-53*

Many students who suffer from math anxiety have little confidence in their ability to do mathematics and tend to take the minimum numbers of required mathematics courses, which has greatly limited their career choice options (1). Mathematics anxiety involves negative cognitions (2), avoidance behaviors, feelings of pressure and performance inadequacy that interfere with the manipulation of numbers and solving mathematical problems in a wide variety of ordinary life and academic situations (3 and 4).

Results from researches had shown that mathematics anxiety was a significant factor of learning success (5). Individuals with high mathematics anxiety tend to perform poorly in an upper-level college statistics course. Furthermore, individuals with mathematics anxiety have shown to avoid environments and careers that require the utilization of mathematics skills (6). Clute (7) and Hembree (8) also have found that students who have a high level of mathematics anxiety have lower levels of mathematics achievement. They have also noted that math's anxiety seriously constrains performance in mathematical tasks, and reduction in anxiety is consistently associated with improvement in achievement. Therefore, for studying the nature of mathematics anxiety and the degree of its presence for

intervention planning and instructional delivery, the measurement of this construct is critical (4,8 and9).

Studies of gender differences and math anxiety have mixed results. Many studies have reported that poor performance in math and math avoidance was more common among female students (10, 11, 12, 13 and 14). Significant differences have been found on the revised Math Anxiety Rating Scale (MARS) even though males and females reported having taken approximately the same number of math courses in high school (12).

However, other studies have found no gender differences (15, 16 and 17). Resnick et al. (16) found that no sex differences existed in math anxiety among college freshmen. In a study of math and implications for women's career choice by Singer and Stake (17), gender differences were not observed in math anxiety and perceptions of the usefulness of mathematics among sophomore college students but females were less likely to choose a math-oriented career goal.

In comparative to instruments of psychological assessment about anxiety, a paucity of research has focused on examining the psychometric properties of math anxiety measures.

A pioneering assessment was a 98-item MARS; which possessed high reliability and validity (18, 19 and 20). However, MARS was too time demanding for students

(21). Following MARS, researchers developed several shorter versions, including the 24-item Math Anxiety Rating Scale-Revised (MARS-R; 22) and the 9-item Abbreviated Math Anxiety Scale (19).

Hopko et al. (19) segregated the revised Math Anxiety Rating Scale into two dimensions using factor analysis of the item responses for: math evaluation anxiety and learning math anxiety. This is consistent with the results of a study by Alexander and Cobb (23) using similar terms: numerical anxiety and math test anxiety. Based on the findings of Hopko et al. (19), it was hypothesized that a two-factor model, comprising orthogonal Learning Math Anxiety (LMA) and Math Evaluation Anxiety (MEA) dimensions, would provide an adequate fit to MARS-R scores endorsed by undergraduate college students. As a control model, an undifferentiated one-factor model was also tested and compared with the two-factor models to determine incremental fit. Our other aim was to examine measurement invariance of the AMAS model across sex using multi group confirmatory factor analysis.

## Materials and Method

### Participants

The AMAS was administered to 298 undergraduate students (133 males and 165 females) of Tabriz University in Iran who majored in different disciplines of human sciences; they were enrolled in entry-level mathematics courses and voluntarily participated in the study. The sample consisted of 133 males and 165 females. College research examination Board approved the research protocol.

### Procedures

While adapting the instruments to Iranian culture and writing the Persian form, we initially translated the scales into Persian. The Persian version of the scales was translated into English by the second author from the Department of English Language Teaching, who specializes in motivation research, and then it was independently back-translated by two lecturers. The independent translations resulted in general linguistic agreement, with only minor differences in wording of the items. Disagreements over wording were solved through discussion by the two psychologists in consultation with the first author.

### Assessment Measures

The instruments used in this study were as follows: Abbreviated Math Anxiety Scale (AMAS) (19); is a 9-item measure of Mathematics anxiety that yields the LMA and MEA subscales, which accounted for 70% of the variance from an exploratory factor analysis using principal components extraction with varimax rotation. Items on the AMAS were responded to using a 5-point Likert-type scale, ranging from 1 (low anxiety) to 5 (high anxiety), with the total score representing a summation of the nine items. The LMA subscale contains five items and measures the learning math anxiety. The MEA subscale contains four items and measures math evaluation anxiety. As indexed by Cronbach's  $\alpha$ , internal consistency in this study was

excellent within the AMAS ( $\alpha = .90$ ), as well as the LMA ( $\alpha = .85$ ) and MEA subscales ( $\alpha = .88$ ).

Students' motivation-to-learn-mathematics (SMOT) scale that covered the four dimensions of motivation to learn mathematics. The two scales, which had 12 and 28 items, respectively, were embedded in a 108-item students' questionnaire of a major study conducted by one of the researchers (24) on 'factors related to the motivation to learn mathematics among secondary school students in Kenya's Nairobi and Rift Valley provinces. Questionnaire items were reviewed and found to be content valid by a panel of educational researchers in Kenya. A pilot test in Nyandarua and Nyeri Districts that have similar students, schools and learning conditions with those in the study area indicated Cronbach alpha reliability coefficients of 0.88 and 0.89 for Mathematics self-concept (MSC) and SMOT, respectively. The researchers visited the 32-selected schools and arranged with head teachers and heads of mathematics departments to group administer the questionnaires to students. The response rate achieved after a series of follow-ups was 98.3%, which the researchers considered satisfactory for the study. Internal consistency in the current sample was satisfactory as well ( $\alpha = .81$ ).

Statistics Anxiety Measure (SAM) (25) is a 23-item questionnaire that comprises six discrete subscales: Anxiety, Performance History and Self-Concept, Expectations, Attitude, and Fearful Behavior. In this study, however, four subscales were utilized. In general, the internal consistent reliability of overall scale ( $\alpha = 0.93$ ) as well as sub-scales ranged from high to excellent ( $\alpha = .82-.95$ ).

### Data analysis

The analyses addressed two main questions. First, which existing factor structure (one and two factor structures) provides an acceptable measurement model for the 9-item AMAS? To address this question, CFA was used to impose each of the two factor structures on two data sets to evaluate each model's goodness-of-fit. Second, is there measurement invariance with respect to gender? To address this question, multigroup CFA was used to test hypotheses about the invariance of the 9-item AMAS across males and females. One-way analysis of variance (ANOVA) was also used to compare gender differences on the subscale of AMAS. Data were analyzed using PASW Statistic 18 and AMOS 18 (26 and 27). PASW was used to analyze descriptive statistics and the reliability of the AMAS. AMOS was used to perform the CFAs of the AMAS analyzing the fit of models and their respective parameter estimates in two distinct stages.

In stage 1, the two models were subjected to a maximum-likelihood CFA using AMOS. First, the nine items of the AMAS were expected to load onto a single latent factor (model 1.). Second, run for the two-factor model was suggested by Hopko et al (19) who reported that a two-factor model provided a better fit to the data than a single factor. In order to rule out the possibility that this model is superior because any two-factor

model would fit the data better than the one-factor model, an alternative two-factor model was tested, with one factor corresponding to the first 4 items and the second factor corresponding to items 5 (model 2). The five items (1,3,6,7,8, and 9) of the Math Anxiety subscale of the AMAS were assigned to the first factor, and one factor corresponded to the four items (items 2, 4, 5, and 8) (Model 3).

In stage 2, multiple group CFA was used to test whether the two-factor structure of the AMAS operate equivalently across both male and female students. This involved comparing the goodness-of-fit  $\chi^2$  of two nested CFA models: one constraining the magnitudes of the factor loadings to be equal for male and female students, and the other omitting this invariance constraint.

Table 2 presents the fit statistics for the models. Several fit indices were examined to evaluate the overall fit of each model:  $\chi^2$  (tests the hypothesis that an unconstrained model fits the covariance or correlation matrix as well as the given model; ideally values should not be significant); Comparative Fit Index (CFI; comparison of the hypothesized model with a model in which all correlations among variables are zero, and where values around .90 indicate very good fit); Root-Mean-Square Error of Approximation (RMSEA; values of .08 or below indicate reasonable fit for the model; Tucker-Lewis Index (TLI) and the incremental fit index (IFI), with values close to .95 being indicative of good fit (28); Akaike Information Criterion (AIC; AIC close to zero reflects good fit and between two AIC measures, the lower one reflects the model with the better fit)(27)

**Results**

**Table 1: Descriptive Statistics for AMAS items and correlations of individual items and subscales/total scale.**

Item	M.	SD	Corrected Item-Subscale Correlation	Corrected Item-Total Correlation
A1 Having to use the tables in the back of a math book	.47	.90	.42	.41
A3 Watching a teacher work an algebraic equation on the blackboard	.72	1.08	.61	.60
A6 Listening to a lecture in math class	.67	1.03	.54	.47
A7 Listening to another student explain a math formula	.67	1.06	.49	.44
A9 Starting a new chapter in a math book	.90	1.19	.57	.55
A2 Thinking about an upcoming math test 1 day before	1.22	1.23	.61	.63
A4 Taking an examination in a math course	1.43	1.30	.66	.66
A5 Being given a homework assignment of many difficult problems that is due the next class meeting	1.43	1.28	.54	.53
A8 Being given a "pop" quiz in math class	1.91	1.40	.58	.45

n = 298 (133 males and 165 females)

**Reliability Estimates**

Descriptive statistics for AMAS items and correlations between each item and their own subscales and between each item and the total scale are illustrated in Table 1. Almost all correlations between individual items and the total scale ranged from .41 to .66. Correlations between individual items and their respective subscales ranged from .42 to .61 for learning mathematics anxiety, from .54 to .66 for mathematics evaluation anxiety.

We computed estimates of internal consistency using Cronbach's coefficient alphas. Scores obtained from the nine-item AMAS had a Cronbach's alpha of .82. The internal consistency estimates of the two factors were as follows: learning mathematics anxiety (five items;  $\alpha = .75$ ), and mathematics evaluation anxiety (four items;  $\alpha = .79$ ). These Cronbach's alpha estimates appear adequate for general research purposes (29).

**Convergent Validity**

We used SMOT and SAM to provide estimates of convergent validity for the AMAS scores. We expected that the scores on the nine-item AMAS, Factor 1-learning mathematics anxiety and Factor 2-mathematics evaluation anxiety, would be negatively correlated with scores from subscale of SMOT. We expected the construct of AMAS to be more closely aligned with subscales of statistics Anxiety Measure; hence, we expected larger correlations between AMAS scores and subscales of SAM scores than between AMAS scores and SMOT scores. As predicted, scores obtained from fearful behavior factor ( $r = .58$ ), attitude factor ( $r = .55$ ) Expectations factor ( $r = .59$ ), and History and Self-Concept ( $r = .48$ ) were positively correlated with scores from AMAS total.

**Table 2: Means, Standard Deviations, and Intercorrelations among the measured variables**

Factor	$\alpha$	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11	12	13
1	.82	9.44	6.79	1												
2	.75	3.43	3.75	.85**	1											
3	.79	6	4.08	.88**	.50**	1										
4	.88	84.95	15.77	-.40**	-.35**	-.35**	1									
5	.74	13.19	3.81	-.37**	-.34**	-.29**	.81**	1								
6	.65	18.26	4.25	-.25**	-.23**	-.21**	.74**	.49**	1							
7	.75	24.98	5.24	-.22**	-.21**	-.17**	.83**	.60**	.47**	1						
8	.72	28.51	6.04	-.46**	-.36**	-.42**	.86**	.61**	.50**	.59**	1					
9	.94	62.53	19.99	.61**	.48**	.57**	-.65**	-.62**	-.37**	-.43**	-.68**	1				
10	.81	18.07	5.96	.58**	.42**	.59**	-.54**	-.50**	-.32**	-.31**	-.60**	.91**	1			
11	.86	24.54	8.86	.55**	.44**	.51**	-.66**	-.62**	-.37**	-.48**	-.65**	.95**	.80**	1		
12	.77	7.24	3.20	.59**	.52**	.50**	-.59**	-.57**	-.33**	-.36**	-.63**	.82**	.60**	.72**	1	
13	.75	12.74	4.07	.48**	.38**	.45**	-.53**	-.53**	-.28**	-.36**	-.54**	.87**	.71**	.76**	.71**	1

Note: N = 298. 1=AMAS, 2= learning mathematics anxiety, 3= mathematics evaluation anxiety, 4= SMOT, 5= interest, 6=satisfaction, 7=relevance, 8= perceived probability of success, 9= SAM, 10= fearful behavior, 11= attitude factor, 12= expectation factor, 13= self concept factor  
\* p < .05. \*\* p < .01.

**Table 3 :Goodness-of-fit statistics and their comparisons for three alternative measurement models for the 9-item AMAS**

Models and Comparisons	$\chi^2$ .	df.	$\chi^2/df$ .	CFI.	TLI.	IFI.	RMSEA.	AIC.	$\Delta$ AIC.	$\chi^2$ difference.
Model 1	153.24*	26	5.89	.84	.78	.84	.13	209.24		
Model 2	176.25*	25	7.05	.81	.73	.81	.14	234.25		
Model 3	60.79*	25	2.43	.96	.94	.96	.07	118.793		
M1-M3									90.44	92.45*
M2- M1									25.01	23.01*
M2-M3									115.46	115.46*

Note: Model 1= One factor; Model B = Two factor split half; Model C= Final hypothesized two-factor model \* P < 0.001.

**Table 4: Results of multi group confirmatory factor analyses across gender**

Model	CMIN	DF	P	CMIN/DF	CFI	IFI	RMSEA
Female	41.60	25	.02	1.66	.96	.96	.06
Male	48.88	25	.003	1.96	.94	.94	.08
Unconstrained	87.70	48	.001	1.83	.95	.95	.05
Measurement weights	103.86	55	.001	1.89	.94	.94	.06
Structural covariances	112.57	58	.001	1.94	.93	.93	.06

Likewise, obtained scores from SMOT total ( $r = -.40$ ), interest ( $r = -.37$ ), relevance( $r = -.22$ ) satisfaction ( $r = -.25$ ) and perceived probability of success ( $r = -.46$ ) were also negatively correlated with obtained scores from AMAS as expected (see Table 2).

**Between-Group Differences**

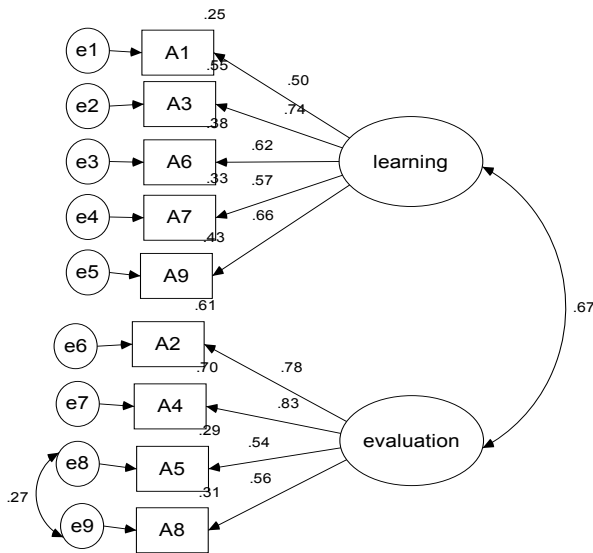
In order to examine possible between-group differences in responses to the AMAS, we ran a one-way analysis of variance (ANOVA) with the subscales of AMAS (learning mathematics anxiety, mathematics evaluation anxiety) as the dependent variable and participants' sex as independent variable. Results showed participants' sex was significantly related to mathematics evaluation anxiety,  $F(1, 296) = 14.51, p < .001$  such that female students had lower scores ( $M = 5.21, SD = 3.59$ ) than male students ( $M = 6.98, SD = 4.44$ ). However, participants' sex was not significantly related to learning mathematics anxiety  $F$

(1, 296) = .574,  $p > .05$ . In other words, male students reported more mathematics evaluation anxiety than female students did.

**Stage 1: assessing measurement models**

To evaluate the goodness-of-fit of three alternative measurement models for the AMAS, CFA was first run for a one-factor solution in which all 9 items loaded on to a single general strengths factor (Model A) and subsequently, it was run for the two-factor model (B) suggested by Hopko et al. (19).

The results of the CFAs for each model are shown in Table 3. In all the analyses the chi-square goodness of fit statistic is large and significant beyond the 0.001 level, rather than being small and associated with a high probability, which would indicate a close fit between model and data. However, this statistic is sensitive to sample size and does not provide a realistic test of the fit of models (27).



**Fig. 1. Confirmatory factor analysis showing the two-factor structure of the AMAS among undergraduate students**

The results of the initial estimation of the one factor model did not provide a satisfactory result with a chi-square value of 153.237 (df =26), which was significant at the  $P < .001$  level. Other fit indices revealed a moderate fit (RMSEA =.13; TLI=.78; CFI=.84; IFI = .84). The two-factor model (model B) where the items are split into two sets to form the factors fits the data no better than the one-factor ( $\chi^2 =78.895$ ;  $p= .001$ ; RMSEA = .08; TLI=.91; CFI=.93; IFI = .93). According to the suggestions of modification indices, covariances were set on the error variances of items 5 and 8 in the internality model based on the reason that items were loaded on one unique factor: mathematics evaluation anxiety. These modifications improved the fit ( $\chi^2 =60.793$ ;  $p= .001$ ; RMSEA = .04; TLI=.94; CFI=.95; IFI = .95)

For the two-factor model, the correlation between the factors is 0.67. Thus, although the two factors were interrelated, the overlap between them was only about 45%, indicating that these need be conceptualized as distinct factors.

We also compared directly the one and two factor models with the  $\Delta\chi^2$  and  $\Delta AIC$  (Akaike Information Criterion) statistics. Both statistics directly compare the fit of the two models after adjusting for differences in the degrees of freedom. In every case the  $\Delta\chi^2$  was significant at .001 and the  $\Delta AIC$  was greater than 25 (conventionally  $\Delta AIC > 15$  is considered very significant). These results again strongly support the superiority of the two-factor model over the one factor and two-factor split half models; subsequently, this model was considered optimal.

**Stage 2: testing gender invariance**

In order to find out whether the model was invariant across gender, a multi-group analysis was conducted. First, the two-factor model was tested separately for the male and female students. A prerequisite for assessing the invariant structure is to first stipulate and test a

baseline model for each group individually. Such a model, which does not include cross- group constrains, should fit the data well in terms of both parsimony and theoretical relevance (27). From the analyses in stage 1, among the two measurement models evaluated, overall fit indexes revealed the multidimensional AMAS model to be the best fitting model available (Model B). Hence, on this basis, the multidimensional AMAS model consisting of two factors was tested on both groups to see if this measurement model was invariant across gender (see table 4).

For females, the two-factor model had goodness-of-fit indexes as follows:  $\chi^2$  (df = 25, n = 165) = 41.60,  $p<.02$ , CFI = .96, RMSEA =.06, IFI = .95. For males, the two-factor model was associated with similar goodness-of-fit indexes:  $\chi^2$  (df = 25, n = 133) = 48.88,  $p<.003$ , CFI = .94, RMSEA =.08, IFI = .94. The unconstrained model (configural model), where factor loadings are allowed to vary between females and males, provided a good fit ( $\chi^2$  [df = 48] = 87.70, CFI = .95, RMSEA = .05). Finally, equality constraints were imposed on factor loadings, variances and covariances. Although chi-square difference tests indicated that constraining regression weights and factor variances and covariances are equal across sexes and led to statistically significant increases of the chi-square value, the fit of the model remained virtually unchanged in terms of the other fit. Nonetheless, the results in table 3 indicate a satisfactory fit for each subgroup and for each of the constraints in the multi-group analysis. It is quite plausible to conclude that the AMAS is invariant across sex.

**Discussion**

The primary purpose of this study was to use confirmatory factor analytic techniques in a sample of young adult college students to explore the fit of the two-factor model of the AMAS proposed by Hopko, Mahadevan, Bare and Hunt. The second aim of the present study was to evaluate the psychometric properties of an Iranian version of the AMAS and to test measurement invariance across sex. Results showed that the AMAS has high internal consistency, with Cronbach’s reaching 0.82. These data are further supported by the parameter estimates of the CFAs, and is generally consistent with previous work showing that AMAS has high internal consistency (19).

The correlational analysis supported the construct validity of the instrument, showing negative association among the AMAS and students’ motivation-to-learn-mathematics. However, there was a high positive correlation between the math anxiety and statistics Anxiety. These results are in accordance with those found by previous works (30, 31, 32 and 33) and they indicate that statistics anxiety is related to test anxiety, math anxiety, and an individual’s history of success and failure experiences in situations involving math.

The present study showed that there was a difference between girls and boys with respect to mathematics

evaluation anxiety and not in learning mathematics anxiety. More specifically, boys reported higher mathematics evaluation anxiety than girls. Whether this finding represents an actual gender difference or is more a function of increased willingness of female students to endorse anxiety symptoms, data suggest that female students are more apt to avoid mathematics courses and careers that require math skills (3). This finding is consistent with that of Pajares and Miller (34), Pajares and Kranzler (35), Shokrani (36) and Kabiri (37) who reported a higher math anxiety for boys. Nonetheless, it differs from the findings of Pajares and Graham (38). In this regard, Betz suggests that the differences in math attitudes between the sexes are the consequence of socialization. Female students may believe to be poor in mathematics and scientific domains (13). Female students who perform poorly may justify their performance as a lack of ability rather than lack of hard work in math. In contrast, male students often may excuse their poor performance in mathematics as lack of hard work (14).

Moreover, like Hopko, Mahadevan, Bare and Hunt (19), the results of our CFA indicate that the most parsimonious best fit to the latent structure of the 9-item AMAS is a two-factor solution assessing learning mathematics anxiety and mathematics evaluation anxiety.

Although the two dimensional structure of the AMAS was invariant across sex, one should be cautious about drawing significant conclusions of such a finding; and further research is required.

Future work should also seek to examine the construct validity of the AMAS, by examining the relationship of math anxiety with related constructs. In particular, it may be useful to investigate the AMAS in relation to other scales that measure test anxiety that had been validated for use among Persian-speaking students.

In conclusion, the present results support the AMAS as a valid and reliable measure of math anxiety among college students within the Iranian context.

## References

- Garry, V.S. The Effect of Mathematics Anxiety on the Course and Career Choice of High School. Ph. D. Thesis (Unpublished), Philadelphia: Drexel University 2005.
- Ashcraft, M. H, Kirk, E.P. The relationships among working memory, math anxiety, and performance. *J Exp Psychol Gen* 2001; 130: 224-237.
- Chipman S.F, Krantz, D.H, Silver, R. Mathematics anxiety and science careers among able college women. *Psychol Sci* 1992; 3: 292-295.
- McMorris, R.F. Review of mathematics anxiety rating scale. *Mental Measurements Yearbook*. Fort Collins, CO: Rocky Mountain Behavioral Science Institute; 2004.
- Ashcraft, M.H. Math anxiety: Personal, educational, and cognitive consequences. *Curr Dir Psychol Sci* 2002; 11: 181-185.
- Clute, P. Mathematics Anxiety, Instructional Method and Achievement in a Survey Course in College Mathematics. *J Research in Mathematics Education* 1984; 15: 50-58.
- Hembree, R. The Nature, Effects, and Relief of Mathematics Anxiety. *J Research in Mathematics Education* 1990; 21: 33-46.
- Alexander, L., Martray, C. The development of an abbreviated version of the Mathematics Anxiety Rating Scale. *Measurement and Evaluation in Counseling and Development* 1989; 22: 143-150.
- Betz, N.E. Prevalence, distribution, and correlates of math anxiety in college students. *J Couns Psychol* 1978; 25: 441-448.
- Llabre, M.M, Suarez, E. Predicting math anxiety and course performance in college women and men. *J Couns Psychol* 1985; 32: 283-287.
- Tobias, S. Math anxiety: Why is a smart girl like you counting on your fingers. *Ms. Magazine* 1976; 92: 56-59.
- Tobias, S. Math anxiety: What you can do about it. *Today's Education* 1980; 61: 26-29.
- Hunsley, J. Cognitive processes in mathematics anxiety and test anxiety: The role of appraisals, internal dialogue, and attributions. *J Educ Psychol* 1987; 79: 388-392.
- Resnick, H., Viche, J., Segal, S. Is math anxiety a local phenomenon? A study of prevalence and dimensionality. *J Couns Psychol* 1982; 29: 39-47.
- Dew, K.H, Galassi, J.P., Galassi, M.D. Math anxiety: Relation with situational test anxiety, performance, physiological arousal, and math avoidance behavior. *J Couns Psychol* 1984; 31: 580-583.
- Hopko, D.R, Mahadevan, R., Bare, R.L., Hunt, M.K. The Abbreviated Math Anxiety Scale (AMAS): construction, validity, and reliability. *Assessment* 2003; 10: 178-182.
- Richardson, F.C, Woolfolk, R.L. Mathematics anxiety. In: Sarason I.G, ed. *Test anxiety: Theory, research, and application*. Hillsdale, NJ: Erlbaum; 1980.
- Singer, J.M. Stake, J.E. Mathematics and 3QIf-esteem: Implications for women's career choice. *Psychol Women Q* 1986; 10: 339-352.
- Pajares F, Urdan T. Exploratory factor analysis of the Mathematics Anxiety Scale. *Measurement and Evaluation in Counseling and Development* 1996; 29: 35-47.
- Plake, B.S., Parker, C.S. The development and validation of a revised version of the Mathematics Anxiety Rating Scale. *Educational and Psychological Measurement* 1982; 42: 551-557.
- Alexander, L., Cobb, R. Identification of the dimensions and predictors of math anxiety among college students. *Journal of Human Behavior and Learning* 1987; 4: 25-32.
- Githua, B.N. Factors related to the students' motivation to learn mathematics among secondary school students in Kenya's Nairobi Province and three districts of Rift Valley Province, doctoral thesis. Kenya: Egerton University; 2001.
- Earp, M.S.R. Fear of Statistics Measure. In a University of Denver Course: *Structural Equation Modeling*. Pilot study of five introductory statistics classes at the University of Denver; 2003.
- Arbuckle, J. L. *Amos Users' Guide Version 18.0*. Chicago, USA: Amos Development Corporation; 2009.

27. Byrne, B. M. Structural equation modeling with AMOS: Basic concepts, applications, and programming, 2nd ed. New York: Routledge Taylor & Francis Group; 2010.
28. Hu, L.T., Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct Equ Modeling* 1999; 6: 1-55.
30. Zeidner, M. Statistics and mathematics anxiety in social science students: some interesting parallels. *Br J Educ Psychol* 1991; 61: 319-328.
31. Benson, J., Bandalos, D. L. Structural model of statistical test anxiety in adults. In: Schwarzer R, Van Der Ploeg HM, Spielberger CD, eds. *Advances in Test Anxiety Research*, Vol. 6. Lisse, Netherlands: Swets and Zeitlinger, Erlbaum; 1989.
32. Benson, J. Causal components of test anxiety in adults: an exploratory study. Paper presented at the annual meeting of the 3 society for test anxiety research. Bergen, Norway; June 1987.
29. Nunnally, J.C., Bernstein, I.H. *Psychometric theory*, 3rd ed. New York: McGraw-Hill; 1994.
33. Sutarso T. Some Variables in Relation to Students' Anxiety in Learning Statistics. Paper presented at the annual meeting of the Mid-South Educational Research Association. Knoxville; November 1992.
34. Pajares, F., Miller, M.D. Role of self-efficacy and self-concept beliefs in mathematical problem-solving: A path analysis. *Journal of Educational Psychology* 1994; 86: 193-203.
35. Pajares, F., Kranzler, J. Self-efficacy beliefs and general mental ability in mathematical problem-solving. *Contemp Educ Psychol* 1995; 20: 426-443.
36. Shokrani, M. Construction and validation of a math anxiety scale for middle school students in Khomeini Shahr and investigating certain related factors to math anxiety. MA Thesis, University of Tehran; 2002.
37. Kabiri, M. The role of math self-efficacy in mathematics achievement with regard to personal variables, MA Thesis. Teacher Training University; 2003.
38. Pajares, F., Graham, L. Self-Efficacy, Motivation Constructs, and Mathematics Performance of Entering Middle School Students. *Contemp Educ Psychol* 1999; 24: 124-139.