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"Research Article"

The development of a self-efficacy scale for mathematical modeling competencies

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Abstract

Mathematical modeling has come into prominence during the last few decades in many countries' mathematics teaching curricula. It combines real life situations with mathematical context. Although evaluating students' mathematical modeling performances with a unique Likert type instrument is questionable, having an instrument about their self-efficacy beliefs in mathematical modeling may help to comment about their ideas related to their competencies in mathematical modeling. The purpose of this study is to develop a reliable and valid measurement scale to determine mathematical modeling self-efficacy of mathematics teacher candidates. For this purpose, the draft and final form of the scale were applied to a total of 562 pre-service elementary mathematics teachers from various public universities in Turkey. The findings of study revealed that the scale is unidimensional according to the results of exploratory factor analysis. The unidimensionality of the scale was validated by confirmatory factor analysis. The reliability of mathematical modeling self-efficacy scale was very high (.97). Finally, it was found that this scale is an appropriate measurement tool to evaluate students' self-efficacy beliefs on their mathematical modeling competencies. Some suggestions related to the scale and for further studies were given at the end.

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1. INTRODUCTION

Mathematical modeling is important part of a real life. People often use statements related to mathematics or geometry, and do calculations for different purposes in their daily life. Mathematical modeling can be defined as a part of real life situation that is expressed mathematically. After the expressions, evaluations are done based on the mathematical model, and it is interpreted again in real life context. During this 'mathematization' process, some

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physical models are built from real life situations, and transformed to mathematical models. From this point of view, models are concepts, which are already in human mind for making sense of complex structures and systems, and their demonstrations (Lesh & Doerr, 2003). The term ‘mathematical model’, whereas, is related to explaining the structural characteristics and working principles of real life situation (Lehrer & Schauble, 2007; Lesh & Doerr, 2003). For example, assume that it is planned to design a car parking area. The aim is to locate parking areas for each car such that there is minimum empty place and maximum number of cars located in the area. A drawing or physical manipulative that demonstrate the real life situation is a simple model. However, a mathematical model is formulas or some other mathematical demonstrations that could be used to find the better parking method. When a simple or real model and mathematical model concepts are used within a process, they are considered as parts of mathematical modeling. Blum (1993) identifies mathematical modeling as a process that consists of the following stages;

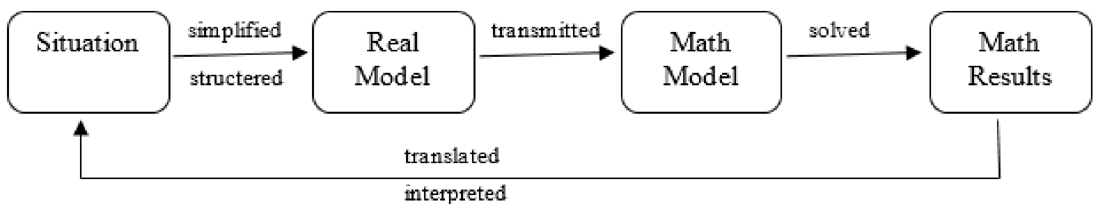

Figure 1. Blum’s stages of modeling process

According to the Figure 1, the real life situation is simplified and structured as a real model that can be interpreted and transmitted into a mathematical model. The process continues with solving the problem to get mathematical results and finally, these results are interpreted and translated to the real life situation. In short, mathematical modeling is a cycle of operating on real life situations (Blum, 1993). Similarly, according to Brown (2002), mathematical modeling is formulating a real world problem, solving it by integrating the real life situation and mathematical manipulation, and checking the result using other real life situations. Lingefjrad (2004) identified that mathematical modeling is the process that includes observing an authentic situation, estimating relationships, applying mathematical analysis, obtaining mathematical results, and interpreting again the model.

Especially, during last few decades, mathematical modeling gained much significance in mathematics education (Blum, 2015). A few fundamental reasons for this situation are the fact that using modeling in mathematics education gives opportunity to understand mathematics more meaningfully, learn mathematics by relating with real life, and eliminate inadequacy of available problems (Erbaş et al., 2014). Haines and Crouch (2001) consider that developing mathematical modeling skills is very crucial and, for this purpose, they suggest that many real life problems should be solved in the classroom, and mathematical modeling courses should be added to the curriculum apart from mathematics courses. Maaß (2006) urged that modeling competencies should be paid attention in the class. It is advised that mathematical modeling needs to be included in mathematics courses at every stage of education beginning from early years of education before high school and college levels (Lehrer & Schauble, 2003).

In general manner, mathematical modeling is the ability to make transitions between real world and mathematical world (Crouch & Haines, 2004). Although there are different approaches based on different theoretical frameworks, there is no consensus on mathematical modeling approaches in the literature (Kaiser & Sriraman, 2006). Though Lesh and Doerr (2003) argue it as a new paradigm beyond the constructivism, Haines and Crouch (2007) regarded modeling as the transition between mathematics and real life. Kaiser and Sriraman (2006) classify modeling approaches that constitute bases for international studies as realistic and applied modeling, contextual modeling, educational modeling, socio-critical modeling, epistemological or theoretical modeling, and cognitive modeling.

Another classification is made based on the aim of using modeling in mathematics education. *Modeling as the purpose of teaching mathematics* and *modeling as a means to teach mathematics* are two general approaches depending on the aim of use (Galbraith, 2012; Gravemeijer, 2002; Niss, Blum, & Galbraith, 2007). Although in the first one the main objective is to develop models and use this models to improve students' mathematical modeling abilities; in the second one the aim is to use mathematical modeling to teach mathematical models and contexts (Erbaş et al., 2014). According to Haines and Crouch (2007), mathematical modeling needs to be regarded as interdisciplinary rather than considering it solely in the mathematical context. Therefore, it is suggested that mathematical skills and competencies that could be used in other disciplines need to be identified and supported in different ways (Erbaş et al., 2014). In the second approach, modeling is used as a teaching tool and it is called the *emergent modeling* approach (Gravemeijer, 2002). It is a result of Modeling and Modeling Perspectives (MMP) in mathematics education (Lesh & Doerr, 2003) and Realistic Mathematics Education (RME) (Freudental, 1991) approaches. MMP is a theoretical approach based on constructivism and socio-cultural theories. It focuses on teaching, learning and problem solving in mathematics. In the context of MMP, a 'model' is product obtained at the end of a process; 'modeling' is a process that constituting the physical, symbolic, or abstract model of a situation (Erbaş et al., 2014). The theoretical basis of another modeling approach offered by RME is the same as MMP (Freudental, 1991; Gravemijer, 2002). In this approach, 'modeling' is not just transferring authentic problem situations into mathematical language; it is also the process to reveal new relationships by organizing facts included in these authentic situations (Gravemeijer & Stephan, 2002).

In addition to this information related to modeling and some main approaches, it seems to be an important matter to identify the term 'mathematical competency' before discussing about what modeling competencies are. Niss (2004, p.120) defines it as: "Mathematical competence then means the ability to understand, judge, do, and use mathematics in a variety of intra- and extra-mathematical contexts and situations in which mathematics plays or could play a role." Based on this definition, it is important to know about the context of mathematical modeling in detail to understand modeling competencies. Maaß (2006) urges that there is close relationship between modeling competencies and the process of modeling. Blum and Kaiser (1997) evaluate modeling competencies as the objectives that needed to be accomplished during modeling process. Therefore, they consider that the students initially need to *understand the real problem* and *set up a model based on reality*. Then, they *set up a mathematical model from the real model* and *solve mathematical questions within this mathematical model*. Finally, the students should i*nterpret mathematical results in a real situation* and *validate the solution* (Blum & Kaiser 1997).

Ikeda and Stephens (1998), and Profke (2000) have similar understanding of modeling competencies with Blum and Kaiser (1997). However, Profke (2000) gives more coverage to general skills such as being curious instead of competencies like interpreting and verifying than Blum and Kaiser (1997). Although Niss (2004) has similar ideas with Blum and Kaiser about modeling competencies, he differentiates between active modeling and models that have been already prepared. Maaß (2006) develops a holistic point of view and stated that modeling competencies are more competencies than just following steps of modeling process. These competencies are sub-competencies to carry out the single steps of the modeling process, metacognitive competencies, competencies for structuring real world situations, competencies for urging modeling process, and competencies for seeing different solutions of the real world problem and developing positive attitude (Maaß, 2006).

On the other hand, the researchers such as Ross Crouch, John Davis, Andrew Fitzharris, Chris Haines, John Izard, Ken Houston, and Neville Neill define mathematical modeling skills at a micro level and stated them as follows (Lingefjrad, 2004): Identifying and simplifying the given information, making the aim explicit, formulating the problem, identifying variables, parameters, and constants, formulating mathematical expressions, selecting a mathematical model, using graphical representations, and comparing with real life situation and controlling the process. It could be seen that these competencies specified by Lingefjrad (2004) are all included in the sub-competencies suggested by Blum and Kaiser (1997). In the present study, mathematical modeling competencies are regarded at micro level. The main reason for not using the framework suggested by Maaß (2006) is the fact that each sub-competency is not specified well and it is difficult to discriminate between them implicitly. Therefore, Blum and Kaiser's (1997) framework that includes all competencies specified by Lingefjrad (2004) was used to develop item clauses. However, modeling is time consuming to apply in the classroom, does not fit the curriculum, makes mathematics lessons more demanding and less predictable, and assessing modeling is challenging. Peer-to-peer assessment, take-home exams and surveys are some tools for measuring and evaluating students' modeling competencies (Lingefjard & Holmquist, 2004). However, due to the complexity of measuring modeling skills with a unique assessment tool, using a survey will be a convenient way of commenting on mathematical modeling 'self-efficacy beliefs' of teacher candidates which is in the scope of this study.

Whether being used as a means or purpose, mathematical modeling has been an important part of school mathematics. In addition to the studies on mathematical modeling and modeling competencies, teachers' self-efficacy beliefs about their modeling competencies seem to be an important subject that might affect their effectiveness in the classroom. Bandura (1997) identifies the term 'self-efficacy' as beliefs of a person about his/her capacity to do and organize intended course activities to attain given objectives. People with high level of self-efficacy effort much to success and they are more patient in problematic situations (Bandura, 1997). It is found that when the learners are at equal levels of ability, the possibility of finishing a given task for learners who believe to do the task is higher than the ones who do not believe (Schunk & Pajares, 2005).

Another important point is the fact that self-efficacy is not an observed skill or competency, it is internal beliefs of a person related to what to do with this skill (Synder & Lopez, 2002, p. 278). In the context of this study, modeling self-efficacy is related to beliefs of students concerning what to do with their mathematical modeling competencies. In other words, it refers to the beliefs of the students about what they can do with their capacity in mathematical modeling. Bandura (1997) states that four main sources of self-efficacy are mastery experiences, the vicarious experiences provided by social models, social persuasion, and physiological factors. According to Bandura (1997), mastery experiences are the most important and effective sources of self-efficacy beliefs. For example, if the students with higher performance on mathematical modeling get higher scores from a modeling course, they will develop positive beliefs in their capacity of this subject. However, although they have higher performance, and they get low scores, then, their beliefs on their ability will decrease and it will directly affect their performance. This means that students' personal experiences influence their self-efficacy (Bandura, 1997).

The vicarious experiences, also called 'modeling', are related to take others as models. When people do not have any judgments about their capacities or have limited experience on a subject, vicarious experiences are very effective on their performances (Bandura, 1997). Social persuasion, another source of self-efficacy, is related to encouragement of parents, teachers, or friends on accomplishing a task or a mission. Physiological factors, the last source of self-efficacy, affect significantly one's belief in their capacity. People with high level of anxiety or stress are in tendency to develop lower self-efficacy when compared to ones with low level of negative emotional and physiological feelings. It is urged that people who are able to control their anxiety or stress have high self-efficacy beliefs (Bandura, 1997).

In education, self-efficacy studies generally focus on the relationship of self-efficacy with academic performance, motivational tools, the fields of profession, the choice of profession, teachers' practices in the classroom, and students' products on given tasks (Pajares, 1997). In mathematics education, self-efficacy is found as one of the most important factors that affect students' mathematics performance (Dede, 2008; Pajares & Graham, 1999). Similarly, students with low level of mathematics performance have low level of self-efficacy (Lee, 2009). This situation justifies the claim of Bandura (1997) related to mastery experiences source of self-efficacy, which is the fact that students' personal experiences influence their self-efficacy.

As justified by some researchers (e.g. Bandura, 1997; Dede, 2008; Lee, 2009; Pajares & Graham, 1999) there is a close relationship between students' performances and their self-efficacies. From mathematical modeling perspective, it seems to be important to assess students' beliefs about their capabilities in mathematical modeling as these competencies have important implications for their mathematical modeling performances. Therefore, the purpose of this study is to develop and verify Mathematical Modeling Self-Efficacy Scale regarding mathematical modeling competencies. Blum and Kaiser's (1997) framework that includes all competencies specified by Lingefjrad (2004) was used to develop item clauses. The validity of the scale is established by structural equation models. Content and construct related validity evidences are obtained by means of these models and the opinions of scholars, teachers, and students. The internal consistency of the scale was interpreted by evaluating Cronbach's and McDonald's reliability coefficients. During the verification process, it is aimed to specify the following questions:

1. What is the validity of Self-Efficacy Scale in measuring students' mathematical modeling competencies?
2. What is the consistency level of Self-Efficacy Scale in measuring students' mathematical modeling competencies?

2. METHOD

In the present study, a descriptive research design was used to develop a scale to measure the level of students' mathematical modeling self-efficacy. The indices for mathematical modeling competencies were matched by appropriate expressions and the students were expected to select the degree to agree or disagree with given situation. Therefore, it was aimed to describe students' beliefs and ideas about their mathematical competencies. From these perspectives, the present study represents the characteristics of descriptive studies (Frankel & Wallen, 2011).

2.1. Participants

Participants of the present study were selected from four public universities in Turkey. Each university was selected from different regions including Eastern, Mediterranean, Black Sea and Central Anatolia. The participants were elementary mathematics teacher candidates from all class levels. The reasons for selecting pre-service teachers are that because mathematical modeling is included in almost all levels of education, they need to be aware of their modeling competencies to assist the students effectively, and they meet mathematical modeling activities directly or indirectly during their university education. The study was carried out in three application steps. In the first application, the data were collected from 72 (Female=45, Male=27) pre-service teachers to analyze whether the items work or not in terms of sentence structures and item parameters. The second application was carried out with 180 (Female=127, Male=53) pre-service teachers to explore the structure of the scale by performing an exploratory factor analysis. Finally, the third application was carried out with 310 (Female=230, Male=80) pre-service teachers to confirm hypothetical structure of the scale by performing a confirmatory factor analysis.

2.2. Scale development process

In general manner, the purpose of the present study was to develop a scale to measure an affective construct in mathematics education research. Ryang (2014) suggest following steps to develop a scale for this purpose: Defining research problem and significance of the study, literature review, theoretical framework, collecting data, sample selection, target population, developing/adapting measurement scale, data analysis, reporting the results, and reliability and validity studies. In addition, Crocker and Algina (1986) proposed a more technical scale development plan than Ryang's one and focused on developing/adapting measurement scale, data analysis and reliability and validity studies steps in Ryang's process. In the present study, the scale development process was designed by considering scale development process suggested by Ryang (2014), and Crocker and Algina (1986).

Maaß (2006) criticized that modeling competencies are generally associated with modeling process, and stated that modeling competencies are more competencies than just following steps of modeling process. However, as stated before, each sub-competency is not specified well in Maaß (2006) framework, and it is difficult to discriminate between them implicitly. Many researchers, such as Ross Crouch, John Davis, Andrew Fitzharris, Chris Haines, John Izard, Ken Houston, and Neville Neill define mathematical modeling skills at a micro level (Lingefjrad, 2004). In the present study, mathematical modeling competencies are also regarded at micro level instead of Maaß holistic point of view. Therefore, Blum and Kaiser's (1997) framework that includes all competencies specified by Lingefjrad (2004) was used to develop item clauses.

For each mathematical modeling index (sub-competency) given in Blum and Kaiser (1997, p.9) five to seven items were developed and an item pool consisting of 32 Likert type items was prepared (see Appendix). The appropriateness of these items was controlled by two scholars having their PhD degree in mathematical modeling and other two scholars having their PhD degree in the field of measurement and evaluation in education. The criteria for evaluating the items was suitability of the items with the indices of mathematical modeling competencies, appropriateness of item formats, suitability of item levels for pre-service elementary mathematics teachers. In order to increase the quality of the items and to develop items representing the construct ideally, the scholars were also requested to suggest delete or add new items if possible. After revisions of the scholars, some items were deleted, new ones were written, and unclear items were modified. As a result, Mathematical Modeling Self-Efficacy Scale consisting of 32 items was prepared as the first draft (see Appendix).

2.3. Data analysis

The first draft was applied to 72 students to analyze some basic psychometric properties of items including item-total score correlations, item mean, and standard deviations. By doing this, the researcher had also the possibility of observing how students react to the expressions and students' ideas about the item structures. The results of the preliminary analysis revealed that item parameters were appropriate and none of the items were needed to be deleted except modifying some of them to make more understandable.

Verification process of the scale consisted of two applications. Exploratory factor analysis and confirmatory factor analysis were carried out in each application. In order to have evidence for internal reliability of the scale, Cronbach α and McDonald ω coefficients were calculated. The assumptions of factor analysis were checked before doing this analysis. In order to test the appropriateness of sample size, Kaiser-Meyer-Olkin sample suitably test was done and it was found that the sample size was adequate. When the descriptive statistics of the data were examined, there was not any missing values and outliers. As another assumption for factor analysis, there should not be multicollinearity. Since, principle component analysis was done, this assumption will not create problem and there is no need to check (Tabachnick & Fidell, 2013). In order to check univariate and multivariate normality, Chi-square statistics was evaluated and this assumption was not satisfied ($p<0.05$). For this reason, Robust Maximum Likelihood method was used to estimate the parameters. For data analysis, IBM SPSS 18.0, LISREL 8.80, and Microsoft Office Excel 2010 software were used.

3. RESULTS

In this section, the results of item analysis for preliminary application, validity and reliability studies were reported in detail.

3.1. Item Analysis of Preliminary Application

Before verifying appropriateness of the scale structure on a large trial group, it will be beneficial to observe the suitably of the scale in practice on a small group. For this purpose, the first scale template was applied to 72 students and the feasibility of the items was examined. For item analysis two methods are generally preferred: Simple and Henryson methods. Simple method bases on upper and lower 27% of whole group and it is appropriate for a sample of 300 or more participants. Henryson method is usually used for a sample of 60 or higher participants. When the sample is big enough, the results of two methods are similar. In the present study, descriptive statistics were calculated based on Henryson method due to the sample size of the first application (N=72).

In Table 1, item means (μ), standard deviations (*s*) and item-total score correlations (r_{IT}) are given. According to the results, item means differ from 3.13 to 3.85 and standard deviations differ from 0.72 to 1.16. Item-total score correlations differ from 0.30 to 0.66 and all of them are significant ($p<0.05$). Since, it was aimed to develop a scale with high internal consistency, 0.30 and higher correlations are enough for intended purpose. The mean of the items is higher or lower than the mean of all items by standard deviations that are higher than 0.60, which is lower bound.

Table 1. Descriptive Statistics

Item	μ	*s*	*n*	r_{IT}	*Item*	μ	*s*	*n*	r_{IT}
1	3.76	0.853	71	0.43	17	3.3	0.962	71	0.47
2	3.65	0.937	72	0.51	18	3.85	0.98	71	0.39
3	3.71	0.721	72	0.4	19	3.81	0.839	70	0.5
4	3.46	0.992	72	0.43	20	3.25	1.143	71	0.66
5	3.26	0.904	72	0.61	21	3.38	1.156	72	0.47
6	3.18	1.142	72	0.39	22	3.51	1.061	72	0.37
7	3.63	1.131	72	0.36	23	3.33	0.856	72	0.6
8	3.42	1.196	72	0.44	24	3.64	0.844	72	0.58
9	3.68	0.819	72	0.52	25	3.13	1.055	71	0.3
10	3.51	1.061	72	0.41	26	3.38	1.08	72	0.51
11	3.47	1.007	72	0.5	27	3.55	0.983	71	0.61
12	3.73	0.962	70	0.63	28	3.63	0.941	72	0.39
13	3.44	1.06	72	0.41	29	3.4	0.944	72	0.43
14	3.38	0.868	71	0.53	30	3.24	1.12	72	0.54
15	3.81	0.959	72	0.53	31	3.26	0.934	72	0.54
16	3.32	1.005	72	0.6	32	3.44	1.005	72	0.48

3.2. Validity Studies

Validity is a process in which evidences are collected to support inferences done based on test scores (Cronbach, 1984). According to the well accepted classification, validity consists of content, construct and criterion related evidences. Content validity is related to the fact that the items are a sample of subject and behavior domain (Cronbach & Meehl, 1955). In the present study, scholar views were taken as a rational evidence for content validity. Four scholars' suggestions were taken into account during whole scale development process including forming item pool, modifying or deleting items that are not consistent with mathematical modeling construct. Criterion-based evidence is related to the fact that the test measures what it intended to measure (Cureton, 1951). In order to provide evidence for criterion-based validity, the correlation between developed scale and an already existed scale that measures the same construct is examined. Since there could not be found any scale that measures mathematical modeling self-efficacy, criterion-based validity evidence could not be obtained for the present scale.

Construct validity is related to the construct that test measures instead of criterion scores. Cronbach and Meehl (1955) stated that nomological networks that indicates how constructs will be measured and shows the relationships between each other are essential for construct validity. Campbell and Fiske (1959) made nomological networks more concrete and suggest multi-method multi-trait matrix to show the relationships between variables. They also suggest to analyze convergent and divergent validity evidences together when any concrete criteria do not exist. In the present study, factor analysis was used as an empirical method to provide evidences for the construct validity of the scale. For this purpose, the structure of the scale was explored with exploratory factor analysis after item analysis of preliminary application. The obtained structure of the scale was hypothetically tested with confirmatory factor analysis. After verifying the structure of the scale, convergent validity coefficient was calculated. Due to the unidimensional structure of the scale, divergent validity coefficient could not be calculated.

3.2.1. Exploratory factor analysis.

In order to examine construct validity of the scale, first of all, an exploratory factor analysis was conducted with the data collected from 180 pre-service elementary mathematics teachers. The appropriateness of the data for the analysis was investigated by examining the results of the Keiser-Meier-Olkin (KMO) and Bartlett sphericity tests. According to Tabachnick and Fidell (2013), KMO value should be greater than 0.60 and Bartlett test result need to be significant for an exploratory factor analysis to be conducted. The scale's values for the KMO test was 0.88 and Bartlet test results were significant (χ^2=2044.23, p=0.000). Therefore, it can be said that the data were appropriate for the analysis.

According to Büyüköztürk (2013), the factors that have eigenvalues equal or greater than 1 are assumed to be significant factors. Accordingly, there are 7 significant factors that have eigenvalues equal or greater than 1. Additionally, Büyüköztürk (2013) suggests that if explained variance for a scale that designed as unidimensional is greater than 0.30, it can be accepted enough for ensuring the unidimensionality of the scale. In the present study, the first significant factor has a factor loading value of 0.342. The unidimensional structure of the scale could also be observed from scree plot. The curve of the plot decline dramatically after the first significant factor. This is also an indication for unidimensional structure of the scale. Since the scale was unidimensional as expected, there was no need for rotation.

In the present study, it was aimed that the items which have factor loadings in the first factor are expected to have factor loadings at least 0.50. For this reason, the items (21, 18, 22, 7, 4, 6, 8 and 13) having factor loadings lower than 0.50 were removed from the scale. When these items were deleted one by one, the structure of the scale varied and the items (9, 1, 19, 15, 26, 32 and 2) also had factor loadings lower than 0.50 and were removed from the scale. When all items that were removed from the scale examined they had high relationships with each other and they were lower relationship with the aim of the scale compared to other items according to scholar's views. After reducing dimensions, explanatory factor analysis was repeated with remaining items. Scree plot for dimension reduction analysis is given in Figure 2.

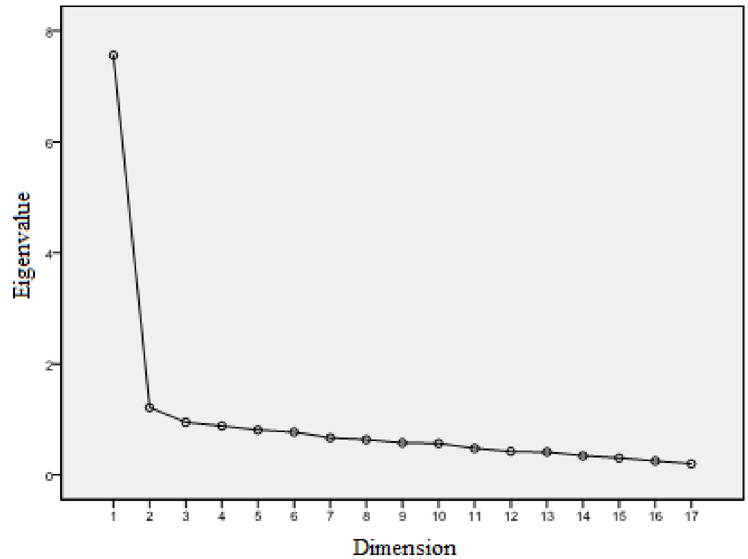

Figure 2. Scree plot

According to the scree plot given in Figure 2, the curve decreases dramatically after the first factor. The second and the other factors have the values very close to each other and the decrease between any two factors is not remarkable. Although the scree plot indicates a unidimensional structure for the scale, it is important to examine component matrix and explained variance proportions.

For the second exploratory factor analysis of remaining 17 items, the scale's values for the KMO test was 0.91 and Bartlett test results were statistically significant (χ^2=1058.85, p=0.000). Therefore, it can be said that the data were appropriate for the analysis. There were two significant factors that have eigenvalues equal or greater than 1. Explained variance for the first factor was 0.445 and hence it indicates a unidimensional scale as observed in the scree plot. All remaining items had factor loadings equal or greater than 0.56 for the first factor (Table 2).

Table 2. Factor Loadings (Λ) and Total Explained Variance

Item	*λ*	*Item*	*λ*	*Item*	*λ*	*Item*	*λ*
5	.776	30	.702	28	.638	25	.616
23	.755	16	.690	11	.638	3	.574
24	.733	27	.682	17	.637	12	.562
31	.729	14	.664	29	.620	10	.558
20	.708						
Eigenvalue = 7.561							
Total variance explained (%) = 44.476							

According to the exploratory factor analysis results, it was concluded that 17 items explained sufficiently mathematical modeling self-efficacy. In order to verify proposed scale structure by this analysis, a confirmatory factor analysis was performed.

3.2.2. Confirmatory factor analysis.

A confirmatory factor analysis was carried out to validate that the scale with 17 items is proper to measure mathematical modeling self-efficacy of pre-service teachers. LISREL 8.80 software was used to perform the analysis and obtain evidences for construct validity of the scale. In order to calculate model parameters, maximum likelihood technique was used (Jöreskog & Sörbom, 2004). Univariate and multivariate normality were checked and it was found that these assumptions were not satisfied as the prerequisite of the analysis. Therefore, a robust method for maximum likelihood technique was performed. Tabachnick and Fidell (2013) suggest carrying out the analysis with a sample of approximately 300 participants. Therefore, the scale with 17 items was applied to 310 pre-service elementary mathematics teachers from different public universities around Turkey.

KMO and Bartlett test results were examined before doing the analysis. According to Tabachnick and Fidell (2013), KMO value should be greater than 0.60 and Bartlett test result need to be significant for a confirmatory factor analysis to be conducted. The scale's value for the KMO test was 0.88 and Bartlett test result was significant (χ^2=1904.52, p=0.000). Therefore, it can be said that the data were appropriate for the analysis.

As shown in Table 3, χ^2 and χ^2/df statistics, the normed fit index (NFI), the non-normed fit index (NNFI; also known as Tucker-Lewis index), the relative fit index (RFI), the comparative fit index (CFI), the incremental fit index (IFI), the goodness of fit index (GFI), the adjusted goodness of fit index (AGFI), the root mean square residual (RMR), and the root mean square error of approximation (RMSEA) were used to interpret the fit of the model to the data (Kline, 2011). Among the modifications given for the decrease in χ^2 values in LISREL output, one of them, which is between items 9 and 10, was done.

Table 3. χ^2 Statistics, Error, and Fit Indices

χ^2	χ^2/df	ρ	RMSEA	NFI	NNFI	RFI	CFI	GFI	AGFI	SRMR	IFI
303.38*	2.55	.000	0.071	0.95	0.96	0.94	0.97	0.87	0.83	0.058	0.97

Notes. ρ<0.01

As shown in Table 3, χ^2 statistics is significant (ρ<0.001) and χ^2/df statistics is 2.55. Although it is advised that χ^2/df value need to be lower than 5 (Anderson & Gerbing, 1984), Kline (2011) stresses that using this value to evaluate the fit of data to the model has not any logical and statistical base. For this reason, interpreting other approximation and fit indices given in Table 3 will be much appropriate. The model RMSEA and SRMR values for the present scale were 0.071 and 0.057, respectively. The acceptable maximum cutoff value for RMSEA is 0.06 and for SRMR it is 0.08 (Hu & Bentler, 1999). However, Steiger (2007) proposes a maximum cutoff value of 0.07 for RMSEA. Hence the model has acceptable fit to the data for RMSEA and SRMR. Inversely, the acceptable value for GFI and AGFI indices is to be greater than 0.80 (Cole, 1987; Marsh, Balla & McDonald, 1988). Since the model GFI and AGFI values for the present scale was 0.87 and 0.83, respectively, the model has again acceptable fit to the data. The model values greater than 0.90 represents good fit, and greater than 0.95 indicates perfect fit of the model to the data (Hair, Anderson, Tatham & Black, 1998). Relative fit indices, RFI, IFI, and CFI have values 0.94, 0.97, and 0.97, respectively. Therefore, RFI indicates well; IFI and CFI have perfect fit of the model to the data. Normed and non-normed fit indices are also interpreted similar to relative fit indices (Hu & Bentler, 1999). Since the model NFI and NNFI values for the present scale were 0.95 and 0.96, respectively, the model has perfect fit to the data.

The item values of standardized factor loadings (λ), unstandardized factor loadings (λ'), t values, standardized error variances (σ_e), unstandardized error variances (σ_e'), and determination coefficients (R^2) were calculated for the theoretical model and given in Table 4.

Table 4. Factor Loadings, t Values, Error Variances, and Determination Coefficients

Item	λ	λ'	t	σ_e	σ_e'	R^2
3	0.64	1	10.55	0.60	0.6	0.40
25	0.57	0.87	11.44	0.67	0.64	0.33
10	0.56	0.9	11.13	0.69	0.74	0.31
17	0.57	0.94	11.03	0.68	0.75	0.32
16	0.61	1.01	11.39	0.63	0.7	0.37
5	0.63	0.93	12.30	0.60	0.53	0.40
11	0.56	0.93	10.75	0.68	0.75	0.32
12	0.58	0.9	10.41	0.66	0.65	0.34
23	0.59	0.9	11.77	0.65	0.63	0.35
20	0.64	0.98	12.27	0.59	0.57	0.41
31	0.61	0.88	11.70	0.63	0.54	0.37
30	0.66	0.91	10.55	0.57	0.45	0.43
24	0.59	0.87	11.71	0.65	0.58	0.35
14	0.64	0.96	10.15	0.58	0.53	0.42
27	0.52	0.78	10.69	0.73	0.67	0.27
29	0.66	1.02	10.52	0.57	0.55	0.43
28	0.58	0.93	10.74	0.67	0.7	0.33

Kline (2011) suggests that the absolute values of standardized factor loadings are expected to be greater than 0.10. In addition, it is also stressed that the values lower than 0.10 indicate small effect; values between 0.30 and 0.50 represent medium effect; and values greater than 0.50 show large effect. Standardized factor loadings for the present scale vary between 0.56 and 0.66 and hence all of them indicate large effect. In addition, *t* values greater than the critical value 1.96 show that all items fit to the unidimensional model. The standardized error variances (σ_e) for the items of the present scale vary between 0.57 and 0.73. These values show that error variances are little higher than medium level. Correspondingly, explained variances vary between 0.37 and 0.43 and they are little lower than medium level. When all findings obtained from the confirmatory factor analysis were interpreted together, it was found that all 17 items fit to the theoretical model.

Convergent validity. The present scale consists of congeneric items. These items do not have equal factor loadings when compared to parallel, tau-equivalent, and essentially tau-equivalent items. Therefore, the reliability and validity coefficients for congeneric items were evaluated differently. McDonald (1985) suggests to use ω coefficient for such items. The value of this coefficient for this scale was calculated as 0.97. Campbell and Fiske (1959) proposed convergent validity to establish construct validity. Convergent validity could be evaluated by using reliability coefficient. $\sqrt{\omega}$ is equal to the correlation between observed and true scores in classical test theory. The value 0.99 indicates that the construct validated by confirmatory factor analysis has a very high convergent validity and this value constitutes a strong evidence for construct validity of the scale. Since the scale was unidimensional, discriminant validity which shows the discrepancy between two dissimilar constructs could not be evaluated.

3.3. Reliability of the Scale

Reliability coefficient was defined differently in the literature. Gulliksen (1950) identified that it is equal to the correlation between observed scores obtained from parallel test forms. Cureton (1958) stated that the ratio of true score variance to the observed score variance corresponds to the reliability coefficient. Lord and Novick (1968) defined it as the square of correlation between true and observed scores. In order to calculate reliability coefficient corresponds to internal consistency of a scale, different reliability coefficients are used according to the equality of item means, standard deviations, error variances, and factor loadings (Yurdugül, 2006). Since items factor loadings of the present scale were not equal, ω coefficient (McDonald, 1985) was used to calculate the reliability of the scale. Kline (2011) suggested that a reliability coefficient greater than 0.90 is reliable at perfect level. As it was calculated in the equation 4, ω internal consistency coefficient of the scale is 0.97. This value indicates that the reliability of the present scale is very high.

In addition to ω coefficient, Cronbach’s α coefficient was also calculated as standardized factor loadings of the items are close to each other. McDonald‘s ω coefficient is equal or higher than Cronbach’s α coefficient in all measurements (Bacon, Sauer & Young, 1995). For the present scale, Cronbach’s α reliability coefficient was calculated as 0.91. This value is the lower bound for the reliability of the scale. Although α is lower than ω coefficient, it also indicates a perfect level reliability for the present scale.

Since McDonald ‘s ω and Cronbach’s α coefficient could have values between 0.00 and 1.00, if the reliability value found is subtracted from 1.00, the new value found indicates total observed score variance arising from random errors (Kline, 2011). When McDonald‘s ω and Cronbach’s α coefficient for the presented scale are subtracted from 1.00, the random error variance is 3% and 9%, respectively. It means that maximum total observed score variance arising from random errors is 0.09. These findings show that the present scale has a very low total observed score variance arising from random errors.

4. CONCLUSIONS AND SUGGESTIONS

The aim of the present study is to develop a self-efficacy scale to measure pre-service elementary mathematics teachers’ belief on their competencies in mathematical modeling. The scale is unidimensional and it is constructed according to Blum and Kaiser’s (1997) mathematical modeling competencies framework that includes all competencies specified by Lingefjrad (2004). The final form of the scale consists of 17 items and they are in the form of Likert format which is scored 1 to 5 points. When the items with negative meaning reversed, the scale scores vary between 17 to 85 points. Higher scale score means higher level self-efficacy of mathematical modeling competencies. Indices for items, and the items included and not included in the final form are given in Appendix. The Turkish version of the final form will be provided to the researchers that are interested in self-efficacy of prospective teachers related to mathematical modeling competencies.

The validity studies revealed that the scale is verified in terms of its content and construct to be measured. The evidences are obtained by taking the ideas of scholars, teachers and students for the content of the scale and it is concluded that the scale measures what it intends to measure. Moreover, exploratory and confirmatory evidences obtained by factor analysis provided strong evidences for the construct validity of the scale. In addition, the reliability analysis revealed high level of internal consistency according to both Cronbach's and McDonald's reliability coefficients. This finding also constitutes an evidence for construct validity of the scale. When all findings are interpreted together, an appropriate tool is developed to measure pre-service teachers' self-efficacy beliefs on their mathematical modeling competencies.

Since assessing mathematical modeling performances is more complicated than expected (Blum, 1993; Lingefjard & Holmquist, 2004), this scale is considered to be a convenient tool that could be used in the field of mathematical modeling. Scholars and teachers can utilize this scale to make interpretations about students' self-efficacies which is one of the most important indicators for performance of the students as justified by some researchers (e.g., Bandura, 1997; Dede, 2008; Lee, 2009; Pajares & Graham, 1999).

In other research studies, it can also be used to investigate on the relationship between modeling performances and students' self-efficacies. Moreover, the scale could be used in mathematical modeling studies for diverse purposes such as examining the effects of other mathematical constructs, their relationship with different demographic variables, etc. In addition, evidences related to criterion-related validity, test-retest, split-half and equivalent form reliability can be collected to enhance the scale. Finally, this scale can be adapted to the high school level for different regions and countries.

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Appendix

Indices for mathematical modeling self-efficacy scale

Indices	*#*	*Item*	*Inclusion*
Competencies to understand the real problem and to set up a model based on reality	1	I could understand real life problem situation by simplifying.	NI
	2	I could make assumptions to understand and interpret real life problems.	NI
	3	I could identify real life situations differently.	I
	4	I have difficulty in planning to solve a real life problem.	NI
	5	I could benefit from relations between variables to make estimations from given situation.	I
	6	I have difficulty in setting up a figure, drawing or model to describe real life situation.	NI
Competencies to set up a mathematical model from the real model	7	I have difficulty in establishing relationships between mathematical models (formula or graphics) and mathematical materials (unit cubes, geometrical strips, etc.).	NI
	8	I could not decide on relevant information to set up a mathematical model.	NI
	9	I could see mathematical relationships in real life situation.	NI
	10	I could reflect on a mathematical model in depth.	I
	11	I could use different materials to set up a mathematical model.	I
	12	I could choose appropriate mathematical notations (graphic, function, etc.) to set up a mathematical model.	I
Competencies to solve mathematical questions within this mathematical model	13	I have difficulty in understanding mathematical and cognitive processes in developing mathematical formulas or notations.	NI
	14	I could compare mathematical models developed for different problem situations.	I
	15	I could decide on how to use mathematics in different problem situations.	I
	16	I could design mathematical models for different mathematical subjects.	I
	17	I could use a formula developed for solving a math problem in developing formulas for similar problems.	I
	18	I could demonstrate a function on a graphical model.	NI
Competencies to interpret mathematical results in a real situation	19	I could interpret mathematical results in social and daily life.	NI
	20	I could apply the solution for a mathematical problem to the real life situations.	
	21	I have difficulty in understanding mathematical formulas or graphics used in other disciplines (physics, chemistry, etc.).	NI
	22	I have difficulty in interpreting mathematical formulas or graphics applied to real life situations.	NI
	23	I could generalize mathematical solutions into different real life situations.	I
	24	I could demonstrate the logic behind a mathematical formula in real life situations.	I
	25	I could develop formulas or graphics that enable to take actions for the future based on a given dataset.	I
Competencies to validate the solution	26	I could validate the model that I developed by mathematical modeling.	NI
	27	I feel confident to demonstrate the accuracy of a mathematical model.	I
	28	I could critically check the solution that I obtained by mathematical modeling.	I
	29	I could review the modeling process after developing a solution for a mathematical problem situation.	I
	30	I could develop alternative solutions during mathematical modeling process.	I
	31	I could develop creative solutions by checking possible mistakes done during modeling process.	I
	32	I could develop problems that could be solved by mathematical formulas or graphics.	NI

Notes.
NI: Items not included in the final form
I: Items included in the final form