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EVALUATION OF A TEST MEASURING MATHEMATICAL MODELLING COMPETENCY FOR INDONESIAN COLLEGE STUDENTS

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ABSTRACT

Background and Purpose: Mathematical modelling competency is one of the vital characteristics in mathematics education. Educational researchers have updated the benefit of modelling as key factor to the study of complexity and modern science. Since many scholars frequently adopt instrument from one cultural background to another, they also offer proof on the issue of validity and reliability. The present paper aimed at validating a mathematical modelling test for secondary prospective mathematics teachers.

Methodology: We utilized a survey approach to examine the factor structure of mathematical modelling test for 202 secondary prospective mathematics teachers, selected by cluster random sampling. Mathematical modeling test was adapted to measure the desired constructs. More importantly, we used exploratory factor analysis (EFA), confirmatory factor analysis (CFA) using AMOS 18 and Rasch measurement model with Winstep version 3.73 to analyze the data.

Findings: The EFA and CFA technique verified that a mathematical modelling test was acceptable for Indonesian prospective mathematics teachers. In addition, Rasch analysis also confirmed that all items fit the criteria well and implied that all items are valid in measuring student mathematical modelling competency. This finding concludes that the mathematical modelling test of Indonesian prospective mathematics teachers have an eight-dimension structure.

Contributions: This present research contributes towards psychometric measure on the reliability and validity of a mathematical modelling test in mathematics education programs.

Keywords: Confirmatory factor analysis, mathematical modelling competency, Rasch measurement model.

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1.0 INTRODUCTION

Mathematical modelling competency has become one of the vital characteristics in mathematics education. Educational researchers have updated the benefit of modelling as key factor to the study of complexity and modern science (Kartal, Dunya, Diefes-Dux, & Zawojewski, 2016). Interestingly, mathematical modelling of situations in contexts is also a primary component of mathematics assessment in the Program for International Student Assessment (PISA) (Niss, 2015). Mathematical modelling competency refers to the cycles of model construction, evaluation, and revision (Blum, Galbraith, Henn, & Niss, 2007; Maaß, 2006). Mathematical modelling entails mathematizing real-world scenarios and developing models to explain a phenomenon under investigation (Albarracín, 2020). Modelling competency is related to the modelling method (Blum et al., 2007; Maaß, 2006). For example, Blum et al. (2007) describe the ability in a given real-life situation to mathematical modelling competency as recognizing relevant variables, relationships, issues or assumptions, to mathematize them in mathematics, and to decode and validate the solution.

Nevertheless, there seems to be consensus that applying a mathematical modelling process in the mathematical classroom is challenging. The learning process of mathematical modelling encompasses a diverse set of objectives and contexts (Abassian, Safi, Bush, & Bostic, 2020). For example, most teachers usually do not discuss the representation of problem situations (modelling) and the representation of mathematical solutions (Murata & Kattubadi, 2012). As for educational researchers, they have paid much more attention on problem solution (e.g., Kushman, Artzi, Zettlemoyer, & Barzilay, 2014; Yew & Akmar, 2016) than problem representation (e.g., Krawec, 2014). In Indonesian setting, a large number of students face difficulty in modelling competency (Jupri & Drijvers, 2016) and even mathematics education pre-service teachers (Widjaja, 2013) have to deal with such difficulties.

Given the importance of modelling competency and its effect on student mathematical competencies, it is vital to understand the application of its appropriate valid measure. Several instruments measure mathematical modeling competency in the current literature (e.g., Haines & Crouch, 2001; Hankeln, Adamek, & Greefrath, 2019; Zöttl, Ufer, & Reiss, 2011). The present research only focused on a mathematical modeling test constructed by Haines and Crouch (2001) although many latest instruments exist for measuring such competency. For example, in a test developed by Zöttl et al. (2011), the method of scoring to "complete modelling task" is not represented (Frejd, 2013), and there is no global fit index for the general suitability of those models. Sub-competencies of mathematical modelling test provided by Hankeln et al. (2019) focus on a written test-manual for grade 9 students. Therefore, the current research focused on the test constructed by Haines and Crouch (2001) as it employed a multiple-choice test format aimed at identifying students' modelling abilities in the early stages of development without having to do a full modelling exercise. Moreover, this test is typically used for a large sample (Lingefjärd & Holmquist, 2005) and has been developed for research (Haines & Crouch, 2005). Analysis of the answers is more objective, efficient, and requires less writing competence (Maaß & Mischo, 2011).

Many scholars provide evidence on validity and reliability issues since many researchers frequently adopt instruments from one cultural background to another. The current research aimed at determining and validating mathematical modelling competency instruments for Indonesian higher education students. Issues relating to validity and reliability of competency in mathematical modelling were revised in previous works (Haines & Crouch, 2001; Izard, Haines, Crouch, Houston, & Neill, 2003; Lingefjärd & Holmquist, 2005). Blomhøj and Kjeldsen (2006) stated that being knowledgeable in modelling competency means one must be able to conduct all dimensions of a mathematical modelling method in a given context independently and with intuition. For example, French and German high-school students come up with two major differences: students' handling of real-world situations and their need for precision (Hankeln, 2020). Riyanto, Putri, and Darmawijoyo (2017) indicated that assumptions, parameters, and critical variables are also unfamiliar to Indonesian students. Therefore, exploratory factor analysis (EFA) is very important because the instruments were adapted from other countries, so the validity and reliability of the mathematical modelling test need to be re-tested. Since mathematical modelling tests are culturally and socially influenced from one context to another, the following research questions were formulated:

1) Does the mathematical modelling test best match the sample in Indonesian setting?
2) Is the mathematical modelling test valid and reliable in Indonesian setting?

2.0 LITERATURE REVIEW

2.1 Mathematical Modelling Competency

Haines (2011) stated the primary factors in mathematical modelling are that students should be in connection with the real world, and the specific instruction of these topics are presented. In the context of curricular discussion, however, there is a different view when the term mathematical modeling is applied. Incorporation of data into examples includes one view of mathematical modelling (Chinnappan & Thomas, 2003) while others believe that mathematical modelling is a conclusion, in itself, not a way to achieve a further mathematical end of learning. Although mathematical modelling has different meanings attached to it, Stillman, Galbraith, Brown, and Edwards (2007) stated that agreement exists that modelling requires a process of formulation, solution, interpretation and evaluation. Blum et al. (2007) stated that students need to define relevant problems, variables, relationships or assumptions in a given actual scenario, mathematize them, interpret and validate the solution in relation to a given situation, and analyze or compare the models.

Previous researchers have therefore indicated that mathematical modelling competency is closely related to the modelling process itself (Blum et al., 2007; Maaß, 2006). This procedure starts with a real setting and finishes with a solution that satisfies the situational requirements (Shahbari & Tabach, 2020). Interestingly, Maaβ (2006) employed a broad mathematical modelling competency framework to capture the definition by including the aspects of cognitive, affective, and metacognitive competencies. Previous research found that modelling competency is positively influenced by metacognitive competencies (Hidayat, Zamri, Zulnaidi, & Yuanita, 2020), solution plan (Nuryadi, 2021), procedural knowledge and problem solving skills (Han & Kim, 2020). At the same time, in a digital climate, modelling practices play a vital role in developing pre-service teachers' metacognitive thinking (Kandemir & Karadeniz, 2021). However, sub-dimensions of metacognitive regulation are more likely to influence solution completeness than metacognitive knowledge sub-dimensions (Bakar & Ismail, 2020).

Modelling problems are not the same as word problems and standard applications. A major difference among those kinds of problem is that the tasks in mathematical modelling do not merely require a straightforward translation and interpretation but also need a process of specifying, formulating, solving and interpreting, proposing, evaluating, and recommending. The key factor in modelling problems is the authentic, complex and open problem (Maaß, 2006). Also, modelling tasks are related to non-routine tasks (Cheng, 2013). The vital demand of the tasks in mathematical modelling is to translate between reality and mathematics (Blum, 2011) because in mathematical modelling, students need to find the correspondence between representations before solving the problem (Pollak, 2011). In Blomhøj's (2011) study, experience working in groups in diverse settings and a comprehensive variety of modelling tasks can promote the many facets of modelling competency.

2.2 Mathematical Modelling Competency Assessment

Determining the competency in mathematical modelling is a much more difficult challenge, as it requires not only evaluating whether the answer is correct or wrong, but also the degree of logical thinking, linguistic skills and effort shown (Lingefjärd & Holmquist, 2005). Also, being competitive in traditional structured mathematics tests does not predict the performance on modelling tasks (Kartal et al., 2016). Due to the difficulty in evaluating mathematical modelling competency, many evaluations of mathematical modelling are used in empirical studies. Written assessments, ventures, hands-on tests, portfolios and competitions are the main modelling assessment approaches used (Frejd, 2013). In particular, the written test makes it "possible to get a snapshot of pupils' mathematical modelling competency at key developmental steps without the student conducting a complete modelling task" as indicated by Haines, Crouch, and Davis (2000).

However, using written test seems to create issues when evaluating student mathematical modelling competency. For example, the written test used in empirical studies focuses on achieved individual skills in mathematical modelling competency (Haines et al., 2000) whereas collaborative work is another important aspect of modelling (Frejd, 2013). Others also documented that when testing students' mathematical modelling competency, they continually return to re-examine and re-define the whole process of mathematical modelling competency (Stillman, 2011). Unfortunately, it is difficult to identify this behavior in students who take examination by written test in a multiple-choice test format (Haines et al., 2000). In the current work, we postulated a conceptual framework based on the theoretical considerations and previous work (Figure 1). The present study predicted that mathematical modelling tests are valid and reliable for populations.

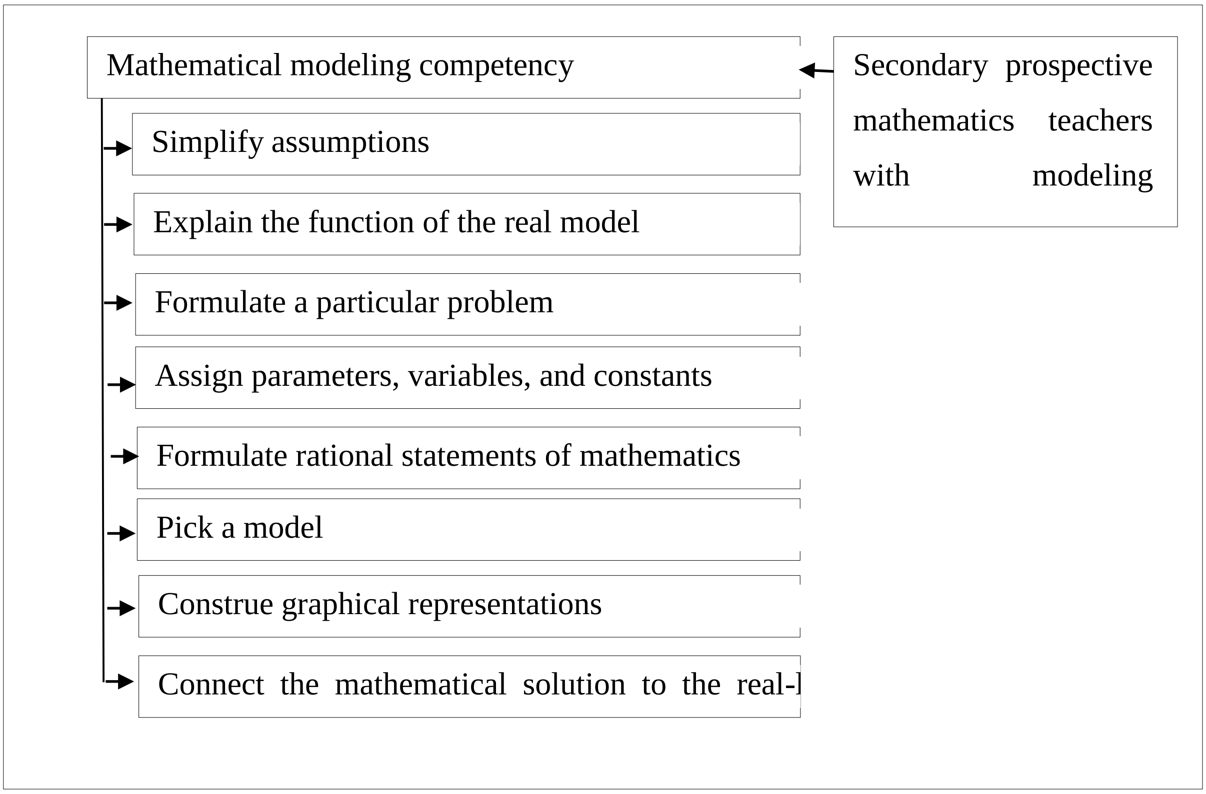

Figure 1: Conceptual framework

In addition, a geometric model is suggested by experts in which teachers need three dimensions: the degree of coverage, the technical level and the radius of action (Blomhøj & Jensen, 2007; Blomhøj & Kjeldsen, 2013; Niss, 2015) to depict and encourage progress in students' mathematical modelling competency. The degree of coverage means that all the definitions and representations of that competency are included in individual competence. The aspects of individual competency will determine it. The technical level refers to the range of conceptual and technical mathematical requirements that can be handled by individuals when activating problem solving skills. The wider the set of requirements that can be handled by the individual, the higher the technical level of individual competence. Radius of action is defined according to the scope of situations in which students can carry out modelling activities or the range of different types of contexts in which they can activate successfully. The radius of action of that person's competency depends on the variety of contexts that the person will activate.

Teachers can conduct the assessment through a dissected approach using multiple-choice questions after each single step in the process of mathematical modeling skills to identify student progress in mathematical modeling for the first dimension (Haines & Crouch, 2001). Furthermore, the format of multiple choices enables a robust concentration of ideas within a reasonable time scale to make it easier to use contextual diversity to prevent distortions from a particular issue in the real world or dependency on a single model (Haines et al., 2000; Haines & Crouch, 2001). Initially, Haines et al. (2000) developed multiple-choice questions (MCQs) of competency in mathematical modelling, then these were extended and used in various environments (see Frejd & Ärlebäck, 2011; Haines & Crouch, 2001; Ikeda, Stephens, & Matsuzaki, 2007; Kaiser, 2007; Lingefjärd & Holmquist, 2005).

Evaluating the radius of action seems to be more problematic because it refers to learner's experience in the diversity and complexity of models (Haines & Crouch, 2010) involving different extra-mathematical contexts and distinct mathematical content fields (Zöttl et al., 2011). Some researchers prefer to evaluate only the degree of coverage and the technical level and to associate certain subjects such as geometry with the radius of action (Zöttl et al., 2011). The possible reason for evaluation difficulties is also linked to a more constricted and narrower school experience than that of university-level students (Haines & Crouch, 2010). Since only one specific mathematical topic has been documented by experts, it seems possible to obtain students' radius of action using the test instrument. In addition, another more pragmatic benefit of a narrowed test instrument may be that it is simple to scale the collected data (Zöttl et al., 2011).

Although the technical level of mathematics is often seen as adequately evaluated outside the modelling activities, it affects modelling that is accessible to students (Haines & Crouch, 2010). Student progress in the technical level of mathematical modelling competency in general framework is regarded as including the improvement on their learning of mathematical concepts through modelling activities (Blomhøj & Kjeldsen, 2013). Similarly, Blomhøj (2011) stated that the technical level of mathematical modelling competency is closely associated with methods involved in the modelling process and the mathematical concept. As such, a proper test instrument should include tasks to distinguish between different levels of competency and therefore requires the use of mathematical tools at various levels (Zöttl et al., 2011).

With regard to the importance of three dimensions in assessing mathematical modelling competence, Zöttl et al. (2011) proposed a test instrument consisting of three different types of items that focus on different sub-processes of modelling activity. They distinguish sub-competencies into four types; type 1-to build up a mathematical model, type 2- intra-mathematical competencies, type 3- the interpretation and the validation, and type 4- overall modelling competency. The research findings revealed the superiority of the sub-dimensional scaling. However, they only measure the degree of coverage and the technical level, while the method of scoring to “complete modelling task” is not represented (Frejd, 2013). Moreover, there is no global fit index for the general suitability of those models.

3.0 RESEARCH DESIGN

3.1 Participants and Procedure

The present research utilized a descriptive survey (Cohen, Manion, & Morrison, 2005; Creswell, 2012; Fitzgerald, Rumrill, & Schenker, 2004; Fraenkel & Wallen, 2009). Cluster random sampling was used (Fraenkel & Wallen, 2009) since the population covers many regions. We selected three universities and evaluated all of the students enrolled in mathematics education programs at those institutions. A total of 202 university students from Indonesia’s mathematics education program participated in the current research. These students have enrolled for several advanced courses such as calculus, geometry, linear algebra, linear programs, and statistics. Hence, it is assumed that they have implicitly learned the mathematical modelling process. The participants were classified as follows: 89.6% females, and 10.4% males. All selected universities finished the written test and 22 multiple-choice items mathematical modelling test during the course hours, based upon voluntary participation.

3.2 Data Collection Tools and Analysis

The mathematical modelling test was used to examine students' mathematical modelling skills. The test was based on a scale adapted from Haines and Crouch (2001), which include eight sub-dimensions, namely simplify assumptions (MMC1), explain the function of the real model (MMC2), formulate a particular problem (MMC3), assign parameters, variables, and constants (MMC4), formulate rational statements of mathematics (MMC5), pick a model (MMC6), construe graphical representations (MMC7), and connect the mathematical solution to the real-life context (MMC8). Two points were awarded for each correct answer to the multiple-choice questions, and one point was awarded for a correct answer or a number of partially correct written answers. False answers were awarded zero point. A total number of 22 items were used in the MCQ mathematical modelling test. In addition, using the binomial probability theorem, it is concluded that the probability of conjecture for ten correction reactions is around 0.0045 (Lingefjärd & Holmquist, 2005).

We used exploratory factor analysis (EFA), confirmatory factor analysis (CFA) and Rasch measurement model to analyze the data. According to Edelen and Reeve (2007), integrating item response theory (Rasch measurement) and classical test theory (EFA and CFA) usually provide complementary association to assess a test or an instrument. We conducted EFA of the 22-item set to examine the assumptions of unidimensionality using SPSS version 23.0. According to Schumacker and Lomax (2010), EFA can examine the number of presented dimensions, detect whether the dimensions are related and identify which observed dimensions are best measured by each single factor. The present research computed the Kaiser-Meyer-Olkin (KMO) value, scree plot, factor loading, Bartlett's value, eigenvalue, and varimax rotation. The KMO measure was used to determine sampling adequacy (Chua, 2014), and Bartlett's test of sphericity was used to confirm the worthiness of the factor model. Factor loading was used to ascertain the meaningfulness of the test (Hair, Black, Babin, & Anderson, 2010) and eigenvalue and scree plot represented the percentage of variance contribution (Chua, 2014). Subsequently, we conducted CFA with the validation sample employing AMOS 18 to confirm the unidimensional nature of the mathematical modelling test. Goodness of model-data fit was assessed using chi-square (χ^2) ($p > 0.05$), Tucker-Lewis index (TLI) (TLI > 0.90), comparative fit index (CFI) (CFI > 0.90), and Root Mean-Square Error of Approximation (RMSEA < 0.08) (Awang, 2012). We also employed Cronbach's alpha coefficients ($\alpha > .60$), composite reliability (CR > .60) and average variance extracted (AVE > 0.50) (Awang, 2012) in the present study.

In order to confirm the reliability and validity of the mathematical modelling competency instrument, Rasch measurement model which is part of the item response theory was employed. Rasch analysis gained its popularity in instrument validation in education field (DeVellis, 2012; Ishak, Osman, Mahaiyadin, Tumiran, & Anas, 2018). The theory is based on two principles: high achievers have a high possibility to respond to all items correctly, and easier items have the tendency to be answered correctly by all respondents (Bond & Fox, 2015). We conducted this analysis by utilizing Winstep version 3.73 to estimate the reliability, separation, fit statistics, unidimensionality and item bias.

4.0 RESULTS

4.1 Exploratory Factor Analysis

EFA procedure was performed to consider all the 22 questions comprising eight dimensions of mathematical modelling competency: simplify assumptions about the issue of real world; explain the function of real model; formulate a particular problem; assign parameters, variables, and constants in a model based on a sound understanding of the situation and model; formulate rational statements of mathematics that explain the problem addressed; pick a model;

construct graphical representations; and connect the mathematical solution to a real life context. The Kaiser-Meyer-Olkin (KMO) measure for mathematical modelling test of 0.78 was acceptable, which provided information on the sampling adequacy for each factor. In addition, the Bartlett's test was significant at $\chi^2 = 2024.46$; $p < 0.001$. Accordingly, employing common factor analysis was suitable for this sample. The subsequent stage was to recognize the scores of the percentage of variances, extraction communalities, factor loading and eigenvalues. In the present research, all question communalities ranged from .18 to .50 (> 0.50) across sub-samples for adequate explanation.

A number of eight dimensions was retained in the study because of the eigenvalues over 1 which emerge from the EFA procedure. Together these eight-dimension structures accounted for about 75.99% of total variance. The first dimension was labeled as simplify assumptions about the issue of real world, with three questions, accounting for 10.08% of the total variance. The second dimension was labeled as explain the function of real model, with three questions, accounting for 8.64% of the total variance. The third dimension was labeled as formulate a particular problem, with three questions, accounting for 7.43% of the total variance. The fourth dimension was labeled as assign parameters, variables, and constants in a model based on a sound understanding of the situation and model, with three questions, accounting for 6.00% of the total variance. The fifth dimension was labeled as formulate rational statements of mathematics that explain the problem addressed, with three questions, accounting for 4.67% of the total variance. The sixth dimension was labeled as pick a model, with three questions, accounting for 6.69% of the total variance. The seventh dimension was labeled as construe graphical representations, with two questions, accounting for 27.46% of the total variance. The eighth dimension was labeled as connect the mathematical solution to a real-life context, accounting for 4.99% of the total variance. In the present research, all the recommended 22 questions for gauging mathematical modelling competency were registered by good loading factors which ranged from 0.71 to 0.89 (> 0.50). In addition, visual - examination of the scree plot which revealed an eight-factor model structure can be determined (Figure 2).

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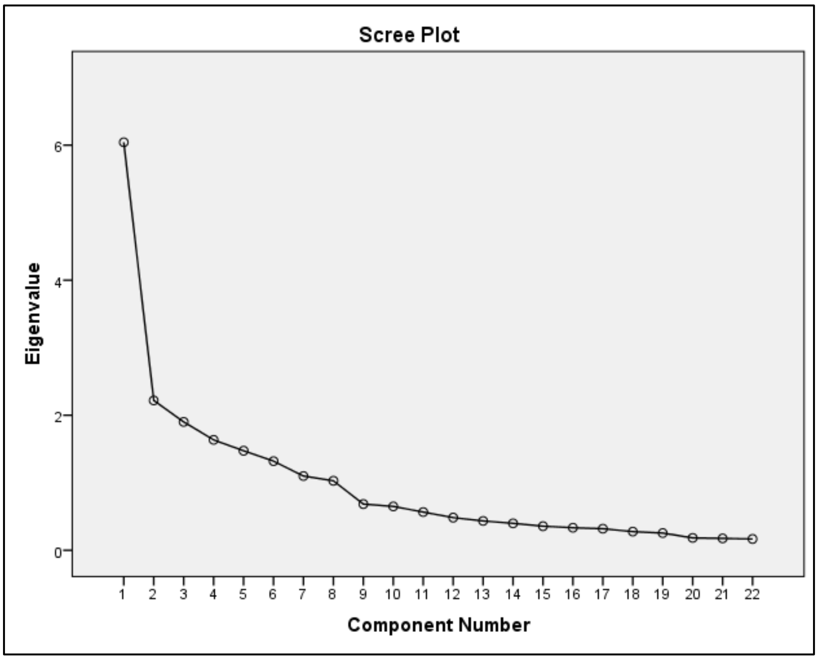

Figure 2: Scree plot for eight dimensions retained on the mathematical modelling test.

4.2 Confirmatory Factor Analysis, Testing the First-Order Factor, and Testing the Second-Order Factor

To conduct the confirmatory factor analysis, the fit statistics were tested employing the maximum likelihood technique. Outputs of the CFA for measurement model of mathematical modelling competency in the validation sample of the 22 questions in the present research showed an acceptable model-data fit ($\chi^2(202) = 309.874$, $p = .00$, $\chi^2/df = 1.712$, CFI = .931, TLI = .912, RMSEA = .06, SRMR = .06). The factor loadings ranged between .64 and .92, showing that the factor loadings surpassed the desirable criteria of 0.50 (Hair et al., 2010). Hence, the CFA model represented in Figure 3 is the final measurement model that shows the structure of mathematical modelling test in Indonesian setting.

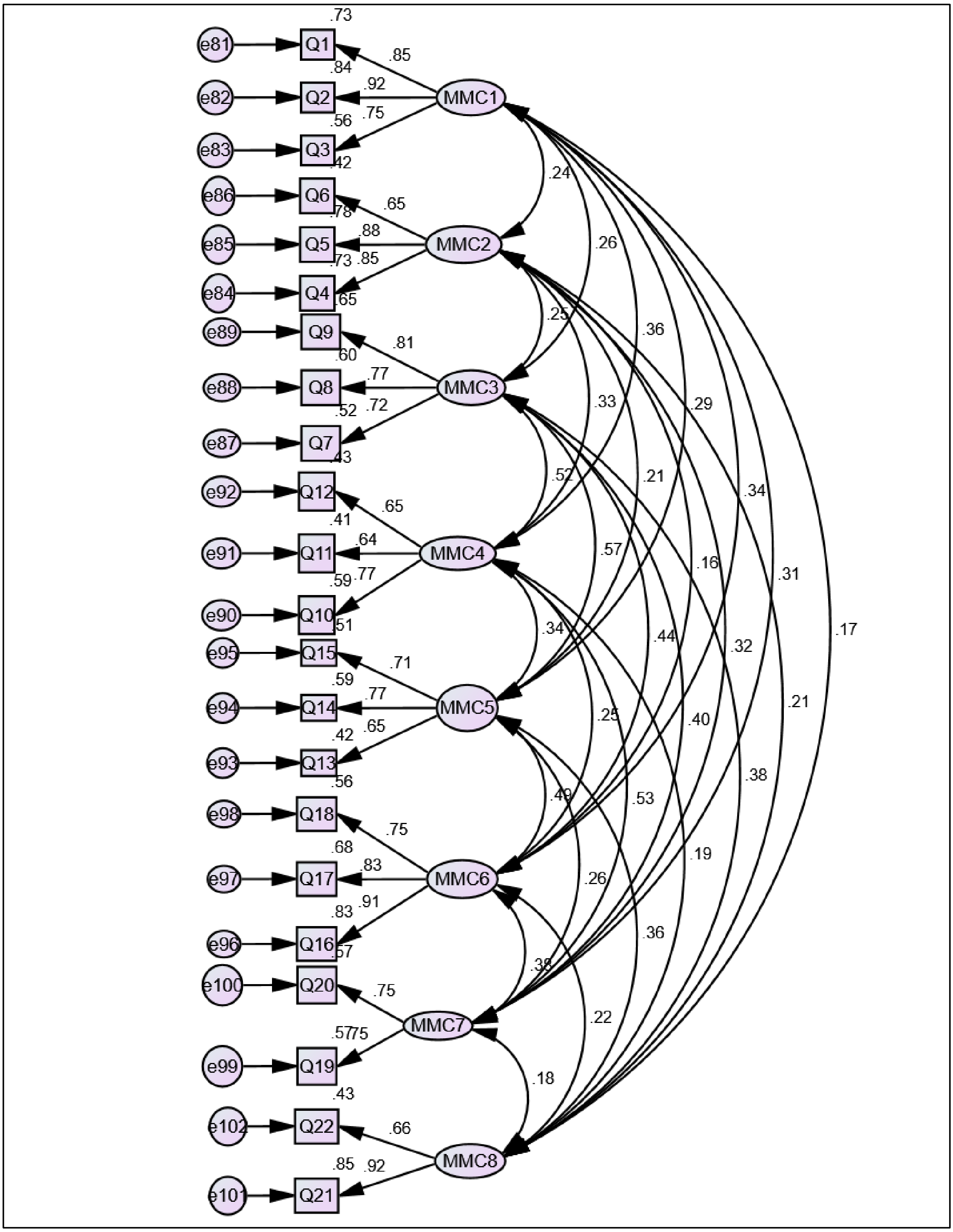

Figure 3: Final measurement model of mathematical modelling test.

A hierarchical factor structure was also examined and hypothesized in the present research. The results of the hypothesized second-order factorial structure for mathematical modelling test are illustrated in Figure 4. A second-order measurement model for mathematical modelling test also showed acceptable model-data fit ($\chi^2(202) = 344.503$, $p = .00$, $\chi^2/df = 1.714$, CFI = .924, TLI = .912, RMSEA = .06, SRMR = .06). The path coefficients for mathematical modelling competency varied among sub-dimensions: MMC1 (.47), MMC2 (.39), MMC3 (.75), MMC4 (.63), MMC5 (.67), MMC6 (.59), MMC7 (.59) and MMC8 (.46).

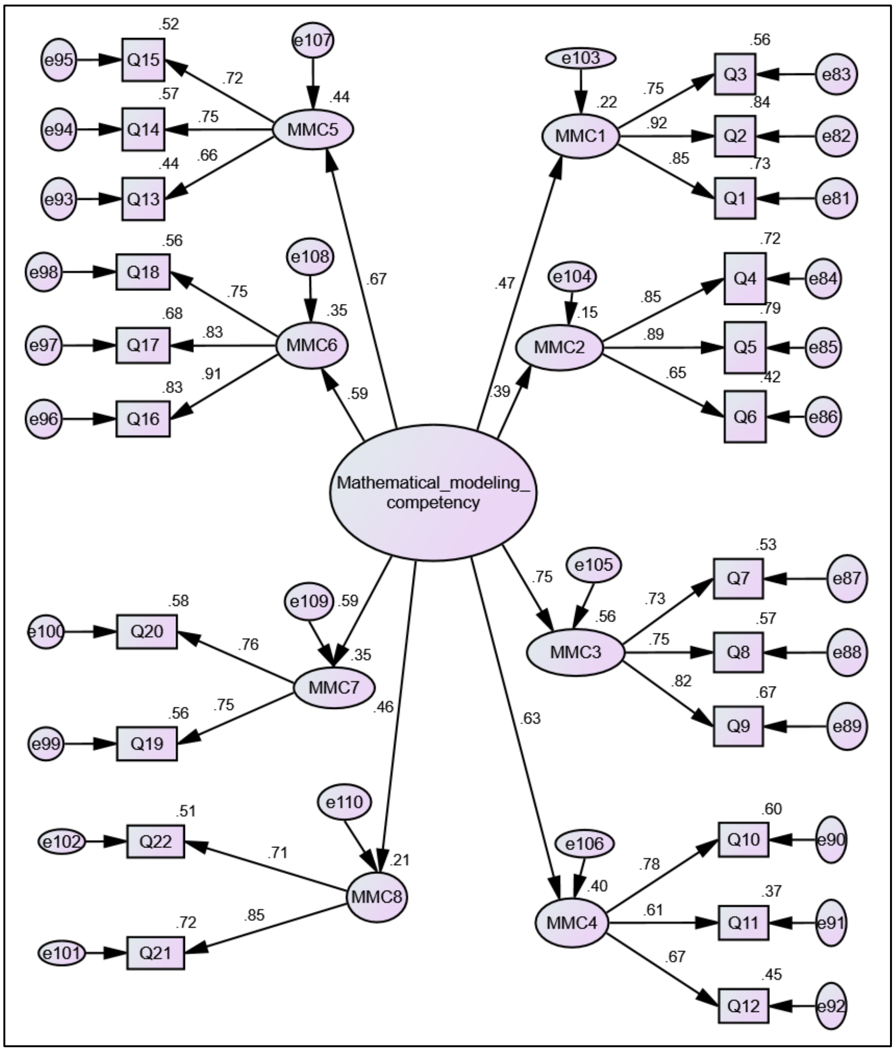

Figure 4: Second-order measurement model for mathematical modelling test

Table 1 indicates model specifications contrasting the first- and second-order measurement models for the mathematical modelling test. Both model specifications fulfilled the standard for good model-data fit.

Table 1: Model specifications for the first- and second-order latent factor

No	Model	χ^2	χ^2/df	CFI	TLI	RMSEA
1	First-order latent factor	309.874	1.712	0.931	0.912	0.060
2	Second-order latent factor	179.830	1.714	0.924	0.912	0.060

Moreover, AVE, CR scores and Cronbach's alpha scores are indicated in Table 2.

Table 2: Reliability analysis for mathematical modeling competency construct

No	Dimension	Cronbach's alpha	CR	AVE
1	Simplify assumptions	.873	.880	0.710
2	Explain the function of real model	.823	.840	0.640
3	Formulate a particular problem	.809	.811	0.589
4	Assign parameters, variables, and constants	.722	.729	0.500
5	Formulate rational statements of mathematics	.754	.758	0.507
6	Pick a model	.863	.871	0.693
7	Construct graphical representations	.720	.725	0.563
8	Connect the mathematical solution to a real-life context	.754	.777	0.641

As seen in Table 2, all AVE scores were higher than 0.50, providing evidence for convergent validity of the mathematical modeling test while all CR scores were greater than .60. Cronbach's alpha scores also gave evidence for the reliability of the mathematical modeling test: .873 for simplify assumptions, .823 for explain the function of the real model, .809 for formulate a particular problem, .722 for assign parameters, variables, and constants, .754 for formulate rational statements of mathematics, .863 for pick a model, .720 for construct graphical representations, and .754 for connect the mathematical solution to a real life context. Table 3 indicates the relationships among the dimensions. All dimensions were significant ($p < .01$).

Table 3: Correlation among dimension

No	Variable	1	2	3	4	5	6	7	8
1	Simplify assumptions	(.842)	.254	.307	.341	.277	.396	.317	.186
2	Explain the function of real model		(.800)	.316	.407	.302	.285	.377	.318
3	Formulate a particular problem			(.767)	.436	.491	.414	.317	.335
4	Assign parameters, variables, and constants				(.707)	.437	.334	.338	.249
5	Formulate rational statements of mathematics					(.712)	.270	.285	.266
6	Pick a model						(.832)	.358	.242
7	Construe graphical representations							(.750)	.210
8	Connect the mathematical solution to a real-life context								(.800)

Note: **Correlation is significant at 0.01 level (two-tailed)

As indicated in Table 3, the highest correlation was between ‘formulate a particular problem’ and ‘formulate rational statements of mathematics’ (r = .491), while the lowest correlation was between ‘simplify assumptions’ and ‘connect the mathematical solution to a real-life context’ (r = .186). The square roots of all AVE scores were greater than the correlations indicated above them or to their right, which support the discriminant validity of the mathematical modeling test.

4.3 The Rasch Model

Based on Rasch analysis, we reported some measures namely reliability, separation, fit statistics, unidimensionality and item bias. The reliability of 22-items was .87 (overall Cronbach alpha), .85 (person reliability) and .92 (item reliability). To ensure its construct validity, the fit statistics to consider were: (a) the value of accepted infit and outfit mean square (MNSQ): 0.5 <MNSQ <1,5 (b) the value of tolerated infit and outfit Z-Standard (ZSTD): -2.0 < ZSTD <+2,0 (c) the value of accepted Correlation Points (Pt Mean Corr): 0.4 < Pt Measure Right < 0.85 (Boone, Staver, & Yale, 2014) (Table 4).

Table 4: Goodness of model fit

Item	Infit		Outfit		
	MNSQ	ZSTD	MNSQ	ZSTD	Pt Mea Corr
1	0.96	-0.5	0.98	-0.2	0.49
2	1	0	0.93	-0.7	0.55
3	0.98	-0.2	0.94	-0.6	0.56
4	1.09	1	1.07	0.7	0.47
5	1.02	0.3	1.05	0.5	0.47
6	1.37	3.9*	1.26	2.4*	0.47
7	0.96	-0.5	0.93	-0.7	0.55
8	1.04	0.5	0.97	-0.3	0.6
9	0.99	-0.1	0.93	-0.7	0.59
10	0.93	-0.8	0.91	-0.9	0.51
11	0.91	-1.1	0.91	-1	0.47
12	0.89	-1.3	0.9	-0.9	0.52
13	0.94	-0.8	0.99	-0.1	0.44
14	0.83	-2.2*	0.82	-1.9	0.56
15	0.97	-0.3	0.98	-0.2	0.51
16	1.06	0.7	1	0	0.57
17	1.07	0.9	1.06	0.6	0.54
18	1.04	0.5	0.95	-0.5	0.62
19	1.06	0.7	1.18	1.5	0.47
20	1.07	0.8	1.08	0.7	0.5
21	0.92	-0.8	1	0.1	0.43
22	0.95	-0.5	1.05	0.5	0.39

Note: * item with a fit value outside acceptable score

The reliability scores exceeded the minimum score of .65 which imply that the instrument has a good stability of item and person score. The reliability result was in line with the separation index of more than 1, and it explicates that the instrument is able to separate the item and person well (Chan, Ismail, & Sumintono, 2015; DeVellis, 2012).

Based on the result of the goodness of model fit, all items fit the criteria well and implied the validity of those items in measuring student ability. Even though some items such as item 6 and 14 had the ZSTD score exceeding the acceptable criteria, the value appears separately rather than taking place together for MNSQ, ZSTD, and PT Mea Corr (Sumintono

& Widhiarso, 2015). A broad outfit value implies that in terms of the targeted abilities, the item does not discriminate between students and can therefore measure a different construct from the rest of the items. (Liu, Lee, Linn, & Liu, 2011).

5.0 DISCUSSION

The current research aimed at determining and validating a mathematical modelling competency instrument for Indonesian higher education students. The eight sub-dimensions of the mathematical modelling test best-matched the sample in Indonesian context. We found that the mathematical modelling test indicates an acceptable Rasch model property. At the same time, the EFA indicates an eight-factor solution with one factor; 'simplify assumptions about the issue of real world', 'explain the function of real model', 'formulate a particular problem', 'assign parameters, variables, and constants in a model based on a sound understanding of the situation and model', 'formulate rational statements of mathematics that explain the problem addressed', 'pick a model' and 'interpret and connect the mathematical solution to a real life context'. Our results indicate that all eight sub-constructs were unidimensional. The findings of the current study are perfectly consistent with those of previous study (Haines & Crouch, 2001; Haines et al., 2000). Also, the conformity of the test to measure the mathematical modelling competence was also affirmed by the CFA procedure. The results of this study align with the results of previous works (Haines & Crouch, 2001; Izard et al., 2003; Lingefjärd & Holmquist, 2005) and demonstrate that the mathematical modelling test best fit for prospective teachers in this study. We concluded that the similarities between the current study and previous research on sub-constructions of competency in mathematical modelling arise from the higher education background of populations that require complex opinions. Thus, for future research, a mathematical modelling test could be suggested.

The second research question in the present study predicted that the mathematical modelling test is valid and reliable. Both CR and Cronbach's alpha scores provide evidence for the reliability. We found that the reliability of mathematical modelling test for prospective secondary mathematics teachers in Indonesia is widely acceptable as well. The reliability of mathematical modelling test is consistent with prior research (Lingefjärd & Holmquist, 2005). The findings provide strong evidence that the generally accepted mathematical modelling test is strongly global. Therefore, our findings can be employed to notify the use of mathematical modelling test in future studies in mathematics education programs in Indonesia. Further examination of the suitability of this mathematical modelling test may be important. The current research adds to the body of knowledge by providing a reliable and valid mathematical modelling test in mathematics education programs in Indonesian context to measure mathematical modelling competency analyzed using a robust EFA, CFA and Rasch model. However, the use of a reliable and valid mathematical modelling test for secondary school students in Indonesia should be examined in the future.

6.0 CONCLUSION, LIMITATIONS AND FUTURE DIRECTIONS

Mathematical modelling competency has become one of the vital characteristics in mathematics education. Yet the issue of instrument validity and reliability in assessing mathematical modelling competency exists. The present paper aimed at validating a mathematical modelling test for prospective secondary mathematic teachers. The analyses confirmed that the mathematical modelling test consists of an eight-factor structure. The mathematical modelling test is psychometrically reliable and valid in Indonesian setting. An important contribution of the current research is that the results revealed the conformity of the test to measure mathematical modelling competency. Further examination in future research should be conducted to investigate whether or not the mathematical modelling test is psychometrically reliable and valid for the whole population of prospective mathematic teachers. One implication for research and practice is that a university might rely on the EFA, CFA and Rasch results to measure mathematical modelling competency for prospective mathematic teachers. Next implication is that the instrument can be used to evaluate teacher training programs in universities and teaching colleges. Widjaja (2013) highlights the importance of involving teachers in mathematical modelling in education programs as a first experience before expecting them to apply mathematical modelling in their own teaching.

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