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Examining the Invariance of a Measurement Model of Teachers' Awareness and Exposure Levels to Nanoscience by Using the Covariance Structure Approach

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Abstract: The main aim of this study is to examine the measurement invariance of the structural equating model constructed on the Awareness and Exposure subscales of Nanoscience and Nanotechnology Awareness Scale (NSTAS) test for three teacher branches, three school types, and two genders by using the covariance structural analysis to test configural and metric invariances. The other aim of this study is showing how to use the IBM AMOS-24 software package with examples to address the issue of measurement invariance using the covariance structural analysis approach. Study sample was 1039 complete records gathered from science teachers with convenience sampling. Research data were collected in two stages. In the first stage, data were obtained from 624 teachers who participated to the study in the 2015-16 academic year. In the second stage, data were obtained in 2019 from 415 teachers via a link to access to the scale and all the instructions for the NSTAS in 2019. The covariance structures analysis was used to examine the measurement invariance of the scale. The comparative fit index was used to compare the measurement invariance in the measurement model. The study revealed that configural, measurement weight and structural covariance invariances were ensured for branches, school types and genders. Residual invariance was ensured only for gender. As a result, it was concluded that the NSTAS scale was not biased for teacher branches, school types or gender. NSTAS scale is recommended for the purposes of comparing branch, school type and gender groups.

1. INTRODUCTION

Nanoscience and nanotechnology (NSNT) are an abstract and complex topic with various applications resulting from the manipulation of atoms and molecules. Nanotechnology, one of the most promising technologies of the 21st century, utilizes devices, structures, and molecules on the scales of nanometers ranging between 1 and 100 nm (Bayda et al., 2020). The responsible development of nanotechnology that addresses the ethical, legal, and societal issues together with research, commercialization, worker education, and public engagement is assumed to

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determine public trust and the future of innovation driven by NSNT. However, describing a world people cannot see and physically interact needs enhancement of understanding these emerging technologies using science communication/citizen-science to reach its full revolutionary potential. Public attitudes, and reflexive governance are essential to public acceptance of NSNT innovation (Boholm & Larsson, 2019).

It is one of the most rapidly growing/broad multidisciplinary fields in science, technology, life sciences and engineering research/innovation and is founded on the convergence of traditional disciplines to create, study, and apply materials at the nanoscale (Holland et al., 2018). Nanotechnology generates great opportunities for cutting-edge research in science and for innovation in industrial production and affects the everyday lives. Presently science teachers typically have insignificant exposure to NSNT, and few opportunities to understand the basic concepts. Developing countries must take their positions in the world nanotechnology market and industry, so planning for good NSNT training is especially important for developing countries. Depending on new information and how it is presented public attitudes toward NSNT may become unstable at times, show rapid change potential since attitudes depend on values, beliefs, and worldviews rather than on facts (Boholm & Larsson, 2019).

Developments and economic impact on commerce and society have brought nanotechnology education to the forefront. Along this line, developed countries have made NSNT education a priority, with intensive education planning and research at primary level being launched. The significance of awareness should be emphasized as an initial step in all nano education processes. The rapid development and impact of NSNT on economy has led policy makers and educators to focus on nanotechnology education (Laherto, 2010). Integrating a new multidisciplinary science at the interface of different scientific and engineering disciplines into the secondary school is a significant endeavor; however, it can be spread throughout a well-designed secondary science education curriculum. Furthermore, factors affecting awareness and knowledge level of teachers/teacher trainees in NSNT should be determined and analyzed before implementing education programs (Hingant & Albe, 2010; Jones et al., 2013). Communicating NSNT to different levels of students places the teacher at the center of learning and teaching activities for NSNT; a significant responsibility (Hingant & Able, 2010). If teachers are not familiar with NSNT, teaching these topics will be a major challenge for them (Greenberg, 2009). Therefore, teachers need to develop their own knowledge and awareness of NSNT to understand and be able to communicate these issues to their students (Blonder et al., 2014). The responsible development of NSNT to safeguard the environment, human health, and safety, and to ensure that the new technology benefits society, requires citizen involvement, dialog, and participation. These cannot be achieved without teacher education and training in NSNT.

It is provided in AERA, APA, and NCME (2014) as standards for evidence regarding internal structure, “if the rationale for a test score interpretation for a given use depends on premises about the relationship among test items or among parts of the test, evidence concerning the internal structure of the test should be provided.” Theoretical structure of a measuring tool raises the concern whether it works the same in different groups, when the differences between the groups are tested. Ensuring the measurement invariance of measuring tools is neglected in almost all research. As Millsap and Yun-Tein (2004) pointed out, the extension of the analysis to the multiple-population case is less well-known, especially for ordered-categorical data in the literature on factor analysis. As Camilli (2006) pointed out that measurement invariance contributes to validity evidence in that scores from a tool are subject to issues of bias and lack of fairness if invariance does not hold.

Whether the Nanoscience and Nanotechnology Awareness Scale (NSTAS), (İpek et al., 2020) measures the same characteristics for three different teacher branches, three school types, and two genders are determined as sub-groups to test the measurement invariances. When different groups are to be compared, the obtained scores from the scale should not be biased (Tan & Pektaş, 2020). Further investigations are necessary to explain/justify the question of whether the scale items perform similarly across subgroups, and one way to examine this question is through assessing the measurement invariance of a scale (Chung et al., 2016). There are several studies in the literature on measurement invariance for test scores (Arana et al., 2018; Camerota et al., 2018). For a measurement model to have the same structure across different groups, the factor loadings of the items in a scale, and the correlations and variances among the identified factors, should be the same (Tan & Pektaş, 2020). While examining the measurement invariance of a measurement model between groups, the model created at each stage is built on the model created in the previous stage, i.e., the models are nested.

As stated by Byrne (2016, pp. 227-228), "In seeking evidence of multigroup equivalence, researchers are typically interested in finding the answer to one of five questions. First, do the items comprising a particular measuring instrument operate equivalently across different populations? In other words, is the measurement model group-invariant? Second is the factorial structure of a single instrument or of a theoretical construct equivalent across populations? Third, are certain paths in a specified causal structure equivalent across populations? Fourth are the latent means of constructs in a model different across populations? Finally, does the factorial structure of a measuring instrument replicate across independent samples drawn from the same population? This latter question addresses the issue of cross-validation."

As Chung et al. (2016) stated, configural invariance is the fact that factor structures between groups are equivalent. In other words, configural invariance tests that the same pattern of item-factor loadings exists across groups compared, which requires that the same items have nonzero loadings on the same factors. To observe whether the other steps of invariance are ensured, comparisons are made based on the configural invariance values (Cheung & Rensvold, 2002; Vandenberg & Lance, 2000). On the other hand, metric invariance refers to equivalence among factor loadings. Chung et al. (2016) emphasized metric invariance, in addition to configural invariance, requires that unstandardized factor loadings be the same across groups. The scalar invariance is based on the equivalence of factor covariances across groups. Therefore, scalar invariance, addition to configural and metric invariance, factor variances and factor covariances are the same across groups. It is a kind of invariance where factor covariances are equalized across the groups after configural and metric invariances are ensured (Cheung & Rensvold, 2002; Meredith, 1993). Strict invariance requires proof that errors do not vary by group. Strict invariance, addition to configural, metric and scalar invariance, the error variances are the same across groups. It is a type of invariance where all factor loadings, factor variances, factor covariances and error variances are constrained (Cheung & Rensvold, 2002).

In the present study, the stages of identifying configural and metric measurement invariances of NSTAS were realized by using the covariance structural analysis (COVS) approach. In COVS approach of testing measurement invariances, only the variances and the covariances between paired observed variables are used as observed variables.

1.1. Aim of the Study

The very first step in nano education at any level is ensuring the awareness of the teachers (Bryan et al., 2012; Enil & Köseoğlu, 2016). The present study aimed to examine the measurement invariance of the structural equating model constructed on the Awareness and Exposure subscales of NSTAS test for three science teacher branches, three school types, and two genders by using the covariance structural analysis (COVS). In this study we also use the IBM AMOS-24 software package as illustrated with examples to address measurement invariances using the covariance structural analysis approach. This is a significant contribution to the field of science education measurement and assessing since most of the measurement invariance studies are confined purely to the measurement field.

2. METHOD

2.1. The Research Model

This study is a descriptive study, as it is intended to present the present situation in terms of measurement invariance of NSTAS structural model and no variable is manipulated. Details of the scale have been published elsewhere (İpek et al., 2020).

2.2. The Study Group

The sample of the study consists of 1039 complete records (without any missing records) gathered from science teachers. Research data were collected in two stages. The data in the first stage were obtained from 624 teachers in the 2015-16 academic year, used in İpek's (2017) doctoral thesis.

Data in the second stage were obtained during 2019 by using a link to access the NSTAS scale and all instructions. In rare cases the scale was administered face-to-face to the respondents. Convenience sampling approach was used to form the study group. The distribution of the 1039 science teachers to the branches, school types and gender were as follows: Biology 38.5%; physics 31.5%, and chemistry 30.0%; science high school 16.3%, Anatolian high school 56.4% and vocational high school 27.3%; and male 45.4% and female 54.6%.

2.3. Data Collection Instruments

The *Nanotechnology Awareness Instrument* (NAI, Dyehouse et al., 2008, refer to Appendix for the instrument) was adapted into a Turkish version and named *Nanoscience and Nanotechnology Awareness Scale* (NSTAS, refer to Appendix for the scale); validity and reliability of the Turkish version were tested by the authors. The original scale (NAI) assessed changes in higher education student awareness, exposure, and motivation for nanotechnology, as well as factual knowledge about nanotechnology. The nanotechnology awareness subscale measures whether respondents "know something about nanotechnology" and whether they "have heard about nanotechnology and its applications". Awareness is supported by exposure, where respondents' previous exposure to nanotechnology may enhance their awareness and knowledge. NAI consisted of two parts: Items in Part A regarding awareness, exposure, and motivation subscales, and Part B regarding factual knowledge about nanotechnology (Dyehouse et al., 2008). Our version, the NSTAS, has three subscales, the *Awareness* (8 items) and *Exposure* (6 items) subscales adopted from NAI (total of 14 items), and the subscale *Knowledge* developed by the authors. The Awareness (8 items) and Exposure (6 items) subscales were used to perform measurement invariance analysis. The Cronbach alpha internal consistency coefficient of the Awareness (8 items) subscale was found to be .934 and Exposure subscale .845. Stratified alpha reliability coefficient for whole scale (with Awareness and Exposure, 14 items) was found to be .945.

2.4. Data Analysis

The covariance structural analysis approach was utilized to examine the measurement model invariances by sub-groups, explained above. The multivariate normal distribution assumption was tested for each subgroup. The multivariate normal distribution assumption was not met for any subgroup. Therefore, bootstrap estimation with 500 bootstrap samples was used to estimate the model parameters. In testing measurement invariances between the .01 reduction criterion the CFI value (ΔCFI) was used. Based on the conditions for ensuring measurement invariance, this has been accepted as proof for the presence of measurement invariance (Cheung &

Rensvold, 2002). Also, a difference of less than .01 in the ΔCFI index supports the less parameterized model (Chung et al., 2016).

During the analyses, the operations were done via the IBM AMOS-24 package program and explained as follows (Byrne, 2016):

IBM AMOS-24 operations for configural invariance.

1. The groups are defined by selecting the *Manage Groups* function from the *Analyze* menu in the *AMOS program*.
2. Subsequently, the data files are assigned to the defined groups by selecting the *Data Files* function from the *File* menu.
3. The *Emulisrel6* box is ticked by selecting *Estimation* from *Analysis Properties* in the *View* menu.
4. Finally, the analysis is run by selecting *Calculate Estimates* from the *Analyze* menu.

IBM AMOS-24 operations for configural, factor loading, structural variances and measurement residual invariances.

Until the stage of making the predictions, as an addition to the operations mentioned above, the parameters to be predicted in the model are labelled manually or automatically. For automatic labelling,

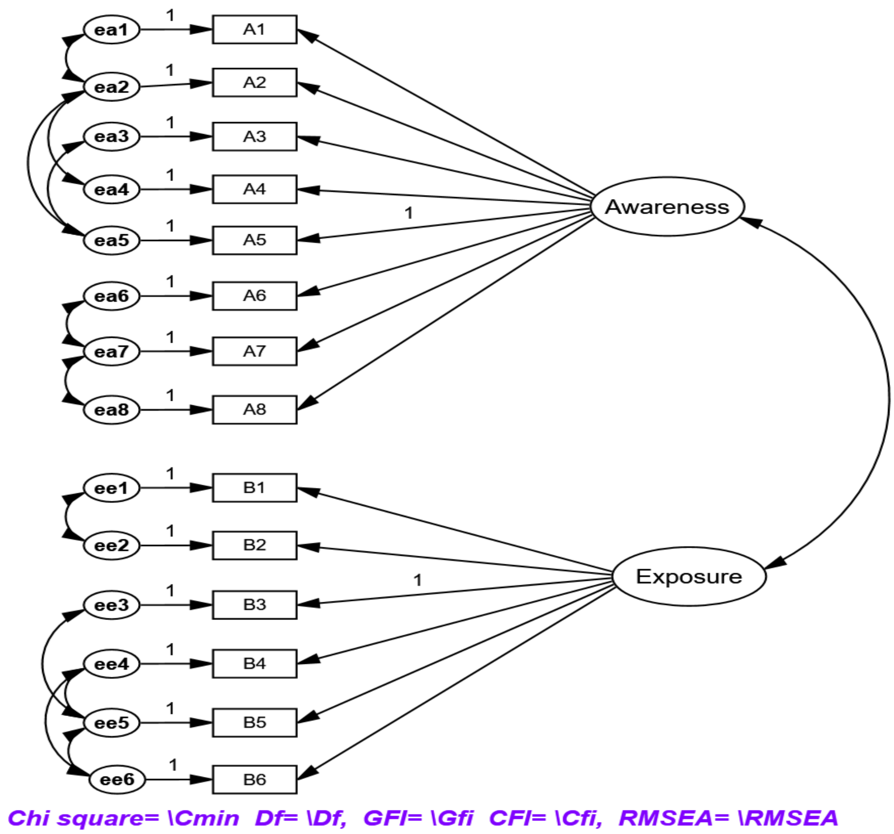
1. *Multiple Group Analysis* function is selected from the *Analyze* menu.
2. The parameters to be constrained are selected in the *Multiple-Group Analysis* dialog box.
3. The analysis is run by selecting *Calculate Estimates* from the *Analyze* menu.

3. RESULT / FINDINGS

3.1. Measurement Model

The baseline measurement model, which is used for eight subgroups, is presented in Figure 1, below.

Figure 1. *The baseline measurement model for the multiple-group invariance of the NSTAS.*



As it seen in Figure 1, *Awareness* latent variable is measured with 8 items (A1 to A8) and *Exposure* latent variable is measured with 6 items (B1 to B6). There are covariance connections between the Awareness and Exposure latent variable and 11 covariance connections between some measurement residual variables in the baseline model. Item A5 was taken as reference for the scale of Awareness latent variable and item B3 for the scale of Exposure latent variable.

3.2. Measurement Invariance by Branch

The goodness of fit indices of the baseline measurement model used for all subgroups created within the scope of the study are presented below. Having good model fit indexes in all subgroups for the baseline measurement model is a prerequisite for invariance analysis.

Step 1: Goodness of Fit Indexes of the Baseline Measurement Model for Branch

The baseline model is presented in Figure 1. In the baseline measurement model based on the branches of teachers, the goodness of fit indexes (Schermelleh-Engel et al., 2003) were found as follows:

- ✓ for Physics teachers X^2_{65}=215.097; X^2/sd=3.309; GFI=0.916; CFI=0.959 and RMSEA=.084;
- ✓ for Chemistry teachers X^2_{65}=175.102; X^2/sd=2.694; GFI=0.927; CFI=0.964 and RMSEA=.074; and
- ✓ for Biology teachers X^2_{65}=216.704; X^2/sd=3.334; GFI=0.931; CFI=0.961 and RMSEA=.076.

In conclusion, the baseline measurement model in Figure 1 displayed a high level of model fit for Physics, Chemistry, and Biology teachers.

Step 2: Configural invariance of the Measurement Model for Branch

As stated by Byrne (2016), to ensure configural invariance, factor loading patterns and the number of factors should be similar for each group. The measurement model based on teachers' branch has provided configural invariance with X^2_{195}=606.903; *X^2/df=3.112;* GFI=.925; *CFI=.961* and *RMSEA=.045.* That is, in this unconstrained measurement model, the factor structure for Physics, Chemistry, and Biology Teacher groups was found to be similar. These results show that the model in Figure 1 is a valid measurement model for all subgroups. The unstandardized estimated parameters (regression weights, covariances, and variances) of three branches for configural invariance are given for each group in Tables 1a, 1b and 1c, below.

Table 1a. *Regression weight estimates for configural model.*

Regression Weights			Estimates		
			Physics	Chemistry	Biology
A7	<---	Awareness	.812**	.624**	1.009**
A6	<---	Awareness	.857**	.710**	.924**
A5	<---	Awareness	1.000	1.000	1.000
A4	<---	Awareness	.984**	1.000**	1.033**
A3	<---	Awareness	.936**	.868**	1.068**
A2	<---	Awareness	.888**	.877**	.941**
A1	<---	Awareness	.959**	.973**	1.101**
B6	<---	Exposure	.402**	.385**	.221**
B5	<---	Exposure	.455**	.473**	.313**
B4	<---	Exposure	.620**	.619**	.450**
B3	<---	Exposure	1.000	1.000	1.000
B2	<---	Exposure	.830**	.820**	.875**
B1	<---	Exposure	.430**	.481**	.437**
A8	<---	Awareness	.921**	.911**	1.093**

*: *p*<.05; **: *p*<.01

Table 1b. *Covariance estimates for configural model.*

Covariance			Estimates		
			Physics	Chemistry	Biology
Awareness	<-->	Exposure	.897**	.650**	.670**
ea7	<-->	ea6	.412**	.438**	.310**
ee6	<-->	ee4	.564**	.565**	.608**
ea5	<-->	ea3	.039	.058	.203**
ee5	<-->	ee3	.093**	-.037	.003
ea4	<-->	ea2	.033	.096**	.113**
ea2	<-->	ea1	.073*	.080**	.114**
ea7	<-->	ea8	.004	.040	.040
ee6	<-->	ee5	.806**	.506**	.611**
ee5	<-->	ee4	.706**	.608**	.725**
ee2	<-->	ee1	.139**	.201**	.050
ea5	<-->	ea2	.046	.036	.030

*: *p*<.05; **: *p*<.01

Table 1c. *Variance estimates for configural model.*

Variances	Estimates		
	Physics	Chemistry	Biology
Awareness	1.172**	1.021**	.749**
Exposure	1.497**	1.570**	1.617**
ea7	.730**	.805**	.696**
ea6	.560**	.636**	.551**
ea5	.422**	.393**	.575**
ea4	.339**	.321**	.383**
ea3	.550**	.527**	.494**
ea2	.372**	.386**	.430**
ea1	.554**	.449**	.534**
ee6	1.056**	1.001**	.825**
ee5	1.070**	1.084**	.911**
ee4	1.193**	1.093**	1.142**
ee3	.477**	.450**	.469**
ee2	.336**	.415**	.254**
ee1	.530**	.442**	.426**
ea8	.522**	.432**	.514**

*: *p*<.05; **: *p*<.01

Step 3: Configural and Measurement Weights Invariance of the Measurement Model for Branch

As Byrne (2016) notes, in testing the measurement, structural and measurement error invariance, the focus is on the parameters, related to the measurement model, structural components and measurement errors, being equal in all groups. The measurement model based on teachers' branch has provided configural and *measurement weights invariance* with X^2_{219}=654.437; X^2/df=2.988; GFI=.919; CFI=.959 and RMSEA=.044. For testing the significant model differences, the CFI change value that we take the criteria was found to be less than .01 (*ΔCFI= .002*). So, difference between configural invariance model and configural and measurement weights invariance model is not significant. In other words, the measurement model with restricted regression weights for Physics, Chemistry and Biology Teacher groups have been found to have good fit indexes with no significant CFI changes. So, measurement weights are equal for Physics, Chemistry, and Biology Teacher groups in the population.

The unstandardized estimated parameters (constrained regression weights, covariances, and variances) of three branches for configural and measurement weights invariance are given for each group in Tables 2a, 2b, and 2c below.

Table 2a. *Regression weight estimates for configural and constrained measurement weights model*.

Constrained Regression Weights			Estimates Physics Chemistry Biology
A7	<---	Awareness	.815**
A6	<---	Awareness	.839**
A5	<---	Awareness	1.000
A4	<---	Awareness	1.004**
A3	<---	Awareness	.967**
A2	<---	Awareness	.900**
A1	<---	Awareness	1.010**
B6	<---	Exposure	.318**
B5	<---	Exposure	.397**
B4	<---	Exposure	.549**
B3	<---	Exposure	1.000
B2	<---	Exposure	.845**
B1	<---	Exposure	.454**
A8	<---	Awareness	.968**

*: p<.05; **: p<.01

Table 2b. *Covariance estimates for configural and constrained measurement weights model.*

Covariance			Estimates		
			Physics	Chemistry	Biology
Awareness	<-->	Exposure	.873**	.622**	.726**
ea7	<-->	ea6	.417**	.431**	.328**
ee6	<-->	ee4	.590**	.588**	.607**
ea5	<-->	ea3	.040	.053	.197**
ee5	<-->	ee3	.089**	-.025	.000
ea4	<-->	ea2	.034	.106**	.106**
ea2	<-->	ea1	.070*	.082**	.110**
ea7	<-->	ea8	.002	.031	.059*
ee6	<-->	ee5	.821**	.529**	.612**
ee5	<-->	ee4	.724**	.639**	.721**
ee2	<-->	ee1	.126**	.194**	.056
ea5	<-->	ea2	.050	.040	.026

*: p<.05; **: p<.01

Table 2c. *Variance estimates for configural and constrained measurement weights model.*

	Estimates		
Variances	Physics	Chemistry	Biology
Awareness	1.121**	.925**	.869**
Exposure	1.502**	1.563**	1.623**
ea7	.732**	.804**	.734**
ea6	.567**	.627**	.559**
ea5	.429**	.407**	.567**
ea4	.340**	.339**	.374**
ea3	.547**	.514**	.497**
ea2	.373**	.393**	.422**
ea1	.548**	.454**	.530**
ee6	1.080**	1.019**	.829**
ee5	1.079**	1.113**	.907**
ee4	1.221**	1.123**	1.137**
ee3	.481**	.470**	.454**
ee2	.318**	.387**	.285**
ee1	.521**	.445**	.425**
ea8	.520**	.428**	.528**

*: p<.05; **: p<.01

Step 4: Configural, Measurement Weight and Structural Covariance Invariance of the Measurement Model for Branch

The measurement model based on teachers' branch has provided configural, measurement weight, and *structural covariance invariance* with X^2_{225}=667.589; X^2/df=2.967; GFI=.918; CFI=.958 and RMSEA=.044. For testing the significant model differences, the CFI change value that we take the criteria was found to be less than .01 (*ΔCFI=.003*). So, difference between configural invariance model and configural, measurement weight and structural covariance invariance model is not significant. In other words, the measurement model with constrained regression weights and structural covariances for Physics, Chemistry and Biology Teacher groups have good fit indexes with no significant CFI changes. So, measurement weights and structural covariances are equal for Physics, Chemistry, and Biology Teacher groups in the population.

The unstandardized estimated parameters (constrained regression weights, constrained structural covariances, other covariances and variances) of three branches for *Configural, Measurement Weights, and Structural Covariance Invariance* model are given for each group in Tables 3a, 3b, and 3c below.

In this model, since we have two structural variables (*Awareness* and *Exposure*), there is one structural covariance and two structural variances to be constrained additionally.

Table 3a. *Regression weight estimates for configural, constrained measurement weights, and constrained structural covariances model.*

Constrained Regression Weights			Estimates Physics Chemistry Biology
A7	<---	Awareness	.815**
A6	<---	Awareness	.838**
A5	<---	Awareness	1.000
A4	<---	Awareness	1.004**
A3	<---	Awareness	.967**
A2	<---	Awareness	.901**
A1	<---	Awareness	1.009**
B6	<---	Exposure	.318**
B5	<---	Exposure	.399**
B4	<---	Exposure	.550**
B3	<---	Exposure	1.000
B2	<---	Exposure	.846**
B1	<---	Exposure	.454**
A8	<---	Awareness	.968**

*: p<.05; **: p<.01

Table 3b. *Covariance estimates for configural, constrained measurement weights, and constrained structural covariances model.*

			Estimates		
Covariance			Physics	Chemistry	Biology
Awareness	<-->	*Exposure*	*.742***	*.742***	*.742***
ea7	<-->	ea6	.420**	.429**	.326**
ee6	<-->	ee4	.594**	.585**	.607**
ea5	<-->	ea3	.041	.056	.195**
ee5	<-->	ee3	.089**	-.025	.001
ea4	<-->	ea2	.033	.105**	.105**
ea2	<-->	ea1	.069*	.082**	.109**
ea7	<-->	ea8	.003	.030	.058
ee6	<-->	ee5	.824**	.526**	.612**
ee5	<-->	ee4	.728**	.635**	.721**
ee2	<-->	ee1	.123**	.195**	.057
ea5	<-->	ea2	.049	.041	.026

*: p<.05; **: p<.01

Table 3c. *Variance estimates for configural, constrained measurement weights, and constrained structural covariances model.*

	Estimates		
Variances	Physics	Chemistry	Biology
Awareness	*.967***	*.967***	*.967***
Exposure	*1.562***	*1.562***	*1.562***
ea7	.735**	.802**	.731**
ea6	.570**	.624**	.558**
ea5	.429**	.412**	.565**
ea4	.339**	.339**	.374**
ea3	.548**	.515**	.494**
ea2	.371**	.392**	.421**
ea1	.546**	.457**	.528**
ee6	1.082**	1.016**	.829**
ee5	1.082**	1.110**	.908**
ee4	1.226**	1.119**	1.137**
ee3	.465**	.500**	.456**
ee2	.313**	.384**	.287**
ee1	.520**	.448**	.425**
ea8	.522**	.427**	.527**

*: $p<.05$; **: $p<.01$

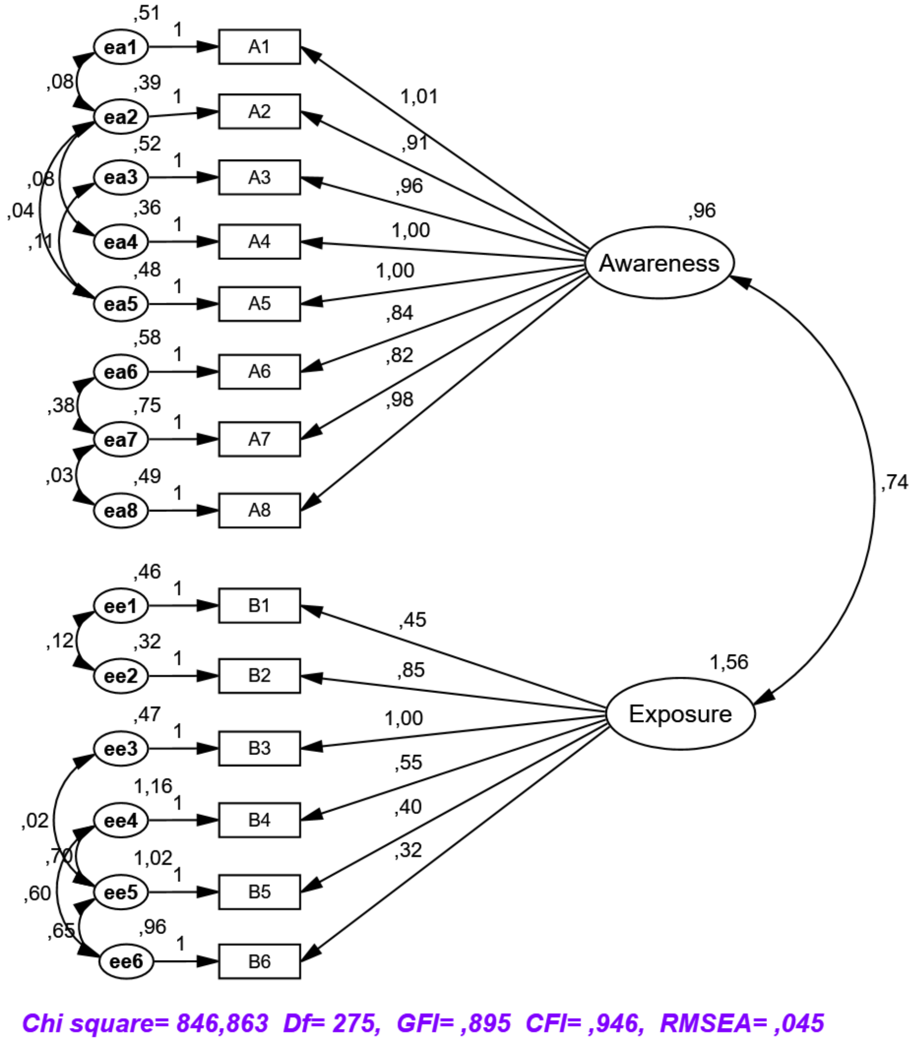
Step 5: Configural, Measurement Weight, Structural Covariance, and Measurement Residual Invariance of the Measurement Model for Branch

The goodness of fit indexes for this model were found to be good with X^2_{275}=846.863; $X^2/df=3.080$; GFI=.895; *CFI=.946* and *RMSEA=.045*. However, for testing the significant model differences, the CFI change value was higher than .01 ($\Delta CFI=.015$). It is clear that, difference between configural invariance model and configural, measurement weight, structural covariance, and measurement residual invariance model is significant. Therefore, measurement residual estimates are not identical for Physics, Chemistry, and Biology Teacher groups in the population.

Because all the model parameters are constrained equal, the unstandardized estimated parameters of the model are given in the path diagram, Figure 2, below.

The main findings regarding the measurement invariance according to the branches are presented in Table 4 below. As can be observed in Table 4, according to the unconstrained (configural) model, the changes in CFI in the models obtained by constraining, in sequence, measurement weights, and structural covariances were less than .01. However, when error residuals constrained the changes, CFI was found to be more than .01. Hence, it was concluded that the measurement model has provided configural, measurement weight, and structural covariance invariance; but did not provide measurement residual invariance across three branches.

Figure 2. *Path diagram for configural, measurement weight, structural covariance, and measurement residual invariance of the measurement model for branch.*



Note: Only 3 covariance estimates (ee5 < -- > ee3=.017 with p=.389; ea7 < -- > ea8=.032 with p=.062; and ea5 < -- > ea2=.037 with p=.013) were not significant, all the other parameters were significant.

Table 4. *Configural, measurement weight, structural covariance, and measurement residual invariance results by branch.*

Model	Number of parameters	X^2	*df*	X^2/df	CFI	ΔCFI	RMSEA
1. Unconstrained (Configural)	120	606.903	195	3.112	.961		.045
2. Measurement Weights	96	654.437	219	2.988	.959	.002	.044
3. Structural Covariances	90	667.589	225	2.967	.958	.003	.044
4. Measurement Residuals	40	846.863	275	3.080	.946	.015	.045

Note: Unconstrained Model: All the parameters are predicted freely.
Measurement Weights Model = All *Factor loadings* are constrained (equated).
Structural Covariances Model = All Factor loadings + *factor variances and covariances* are constrained (equated).
Measurement Errors Model = All Factor loadings + factor variances + factor covariances + *error variances* are constrained (equated).

3.3. Measurement Invariance by School Types

Goodness of Fit Indexes of the Baseline Measurement Model for School Type

In the baseline measurement model based on the school types, the goodness of fit indexes were found to be as follows:

- ✓ for science high school teachers X^2_{65}=163.060; X^2/sd=2.509; GFI=0.885; CFI=0.937 and RMSEA=.095;
- ✓ for Anatolian high school teachers X^2_{65}=328.329; X^2/sd=5.051; GFI=0.927; CFI=0.953 and RMSEA=.083; and
- ✓ for vocational high school teachers X^2_{65}=224.257; X^2/sd=3.45; GFI=0.906; CFI=0.947 and RMSEA=.093.

In conclusion, the baseline measurement model in Figure 1 displayed a high level of model fit for three school types.

3.4. Configural, Measurement Weight, Structural Covariance, and Measurement Residual Invariance of the Measurement Model for School Type

The unstandardized estimated parameters of the model are given with path diagram for school types in Figure 3, below, and the main findings regarding the measurement invariance according to the school types are presented in Table 5 below.

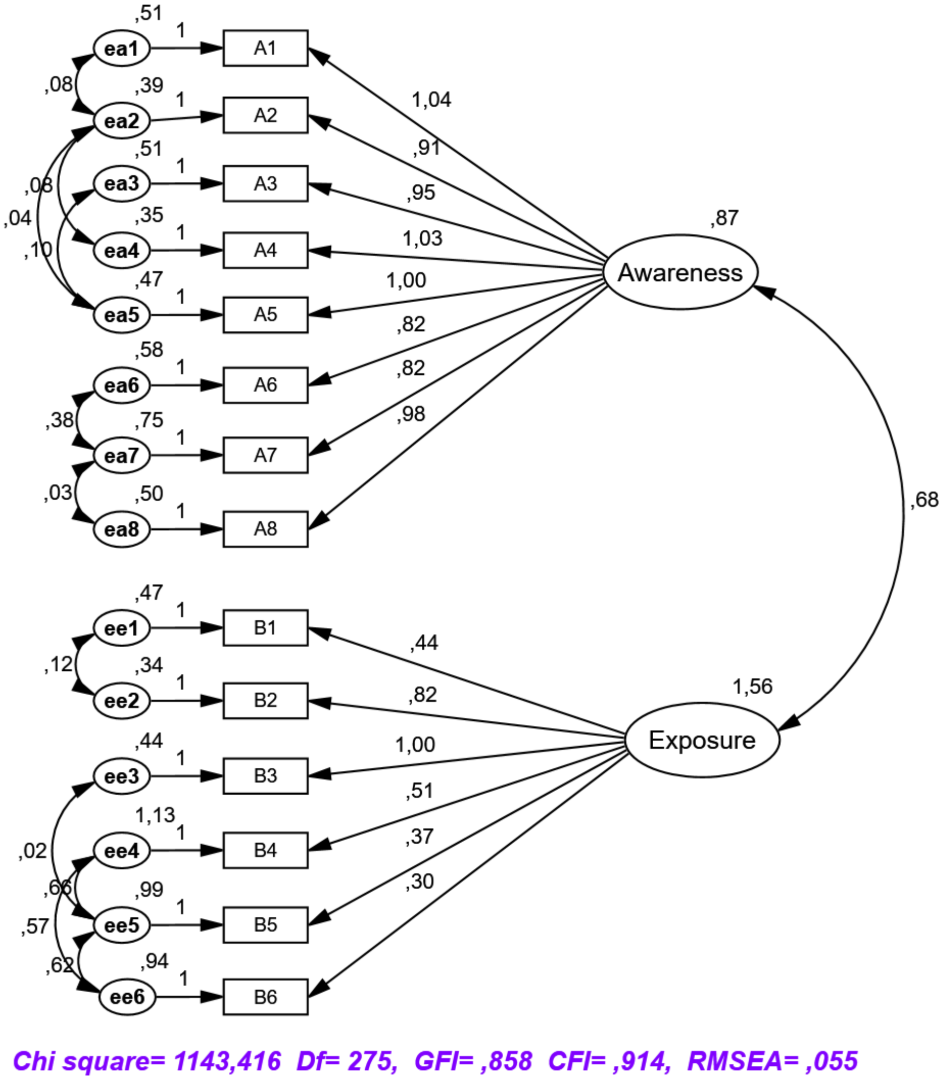
Table 5. *Configural, measurement weight, structural covariance, and measurement residual invariance results by branch.*

Model	Number of parameters	X^2	df	X^2/df	CFI	ΔCFI	RMSEA
1. Unconstrained (Configural)	120	715.646	195	3.670	.949		.051
2. Measurement Weights	96	794.010	219	3.626	.943	.003	.050
3. Structural Covariances	90	820.660	225	3.647	.941	.005	.051
4. Measurement Residuals	40	1143.416	275	4.158	.914	.035	.055

Note: Unconstrained Model: All the parameters are predicted freely.
Measurement Weights Model = All *Factor loadings* are constrained (equated).
Structural Covariances Model = All Factor loadings + *factor variances and covariances* are constrained (equated).
Measurement Errors Model = All Factor loadings + factor variances + factor covariances + *error variances* are constrained (equated).

As it seen in Table 5, according to the unconstrained (configural) model, the changes in CFI in the models obtained by constraining, in sequence, measurement weights, and structural covariances were less than .01. However, when error residuals constrained the changes in CFI was found to be more than .01. Hence, the measurement model has provided configural, measurement weight, and structural covariance invariance; but, not provided for measurement residual invariance across three school types.

Figure 3. *Path diagram for configural, measurement weight, structural covariance, and measurement residual invariance of the measurement model for school type.*



Note: Only 3 covariance estimates (ee5 < -- > ee3=.024 with p=.226; ea7 < -- > ea8=.033 with p=.054; and ea5 < -- > ea2=.036 with p=.015) were not found to be significant, all the other parameters were found to be significant.

3.5. Measurement Invariance by Genders

Goodness of Fit Indexes of the Baseline Measurement Model for Gender

In the baseline measurement model based on the gender, the goodness of fit indexes were found to be as follows:

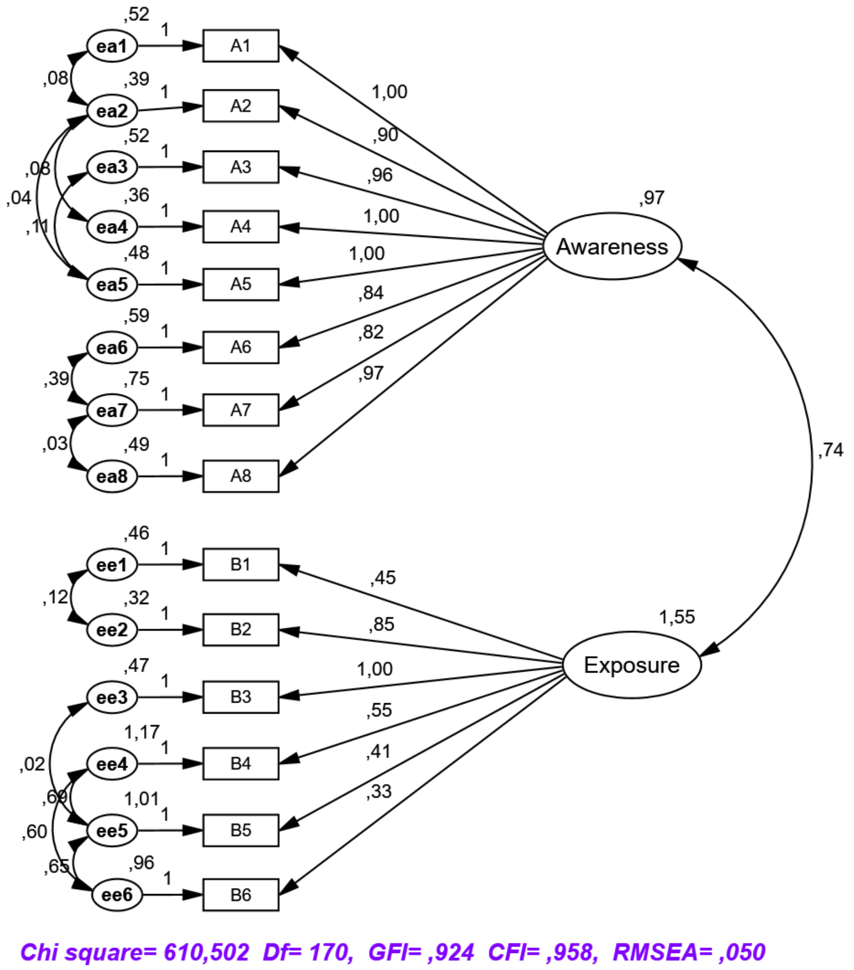
- ✓ for male teachers X^2_{65}=164.122; X^2/sd=2.525; GFI=0.953; CFI=0.978 and RMSEA=.057; and
- ✓ for female teachers X^2_{65}=324.513; X^2/sd=4.993; GFI=0.927; CFI=0.957 and RMSEA=.084.

In conclusion, the baseline measurement model in Figure 1 displayed a high level of model fit for the two genders.

3.6. Configural, Measurement Weight, Structural Covariance, and Measurement Residual Invariance of the Measurement Model for Gender

The unstandardized estimated parameters of the model are given with path diagram for genders in Figure 4, below, and the main findings regarding the measurement invariance according to the genders are presented in Table 6 below.

Figure 4. *Path diagram for configural, measurement weight, structural covariance, and measurement residual invariance of the measurement model for gender.*



Note: Only 3 covariance estimates (ee5 < -- > ee3=.020 with p=.303; ea7 < -- > ea8=.032 with p=.061; and ea5 < -- > ea2=.035 with p=.017) were not significant, all other parameters were found to be significant.

Table 6. *Configural, measurement weight, structural covariance, and measurement residual invariance results by branch.*

Model	Number of parameters	X^2	df	X^2/df	CFI	ΔCFI	RMSEA
1. Unconstrained (Configural)	80	488.635	130	3.759	.966		.052
2. Measurement Weights	68	505.893	142	3.563	.965	.001	.050
3. Structural Covariances	65	507.348	145	3.499	.966	.000	.049
4. Measurement Residuals	40	610.502	170	3.591	.958	.008	.050

Note: Unconstrained Model: All the parameters are predicted freely.
Measurement Weights Model = All *Factor loadings* are constrained (equated).
Structural Covariances Model = All Factor loadings + *factor variances and covariances* are constrained (equated).
Measurement Errors Model = All Factor loadings + factor variances + factor covariances + *error variances* are constrained (equated).

As it seen in Table 6, according to the unconstrained (configural) model, the changes in CFI in the models obtained by constraining, in sequence, measurement weights, structural covariances, and measurement residuals were less than .01. Hence, the measurement model has provided configural, measurement weight, structural covariance, and measurement residual invariance across two genders.

4. DISCUSSION and CONCLUSION

This study investigates the measurement invariance of the Nanoscience and Nanotechnology Awareness Scale (NSTAS) for three teacher branches, three school types, and two genders by using the covariance structural analysis to test configural and metric invariances.

There is need to plan and implement NSNT education at primary, secondary, undergraduate, and graduate levels, since teachers' knowledge and competences are the key to education. Factors affecting awareness and knowledge level of teachers/teacher trainees in NSNT should be determined and analyzed before implementing education programs (Hingant & Able, 2010; Jones et al., 2013). The NSTAS instrument was originally developed by Dyehouse et al. (2008) to promote awareness and factual knowledge among higher education students in the USA about nanotechnology uses, so students become acquainted with nanotechnology as a new field of research and innovation affecting society. The greater objective was to motivate university students to academic and career options in the field.

Braeken and Blömeke (2016) pointed out, "to allow for making group comparisons in terms of correlations with external variables, the stricter requirement of equal factor loadings" across groups (i.e., metric or 'weak' invariance) needs to hold. They also pointed out that "if we wish to directly compare observed scale sum scores between groups, then additionally, the residual item variances would be required to be equal across groups, such that every item can be considered equally reliable across groups". There are some group comparisons and some educational decisions based on these comparisons regarding nanotechnology and nanoscience using NSTAS scores. In terms of objectivity features of scientific research, to test whether the structural validity or the measurement model of the NSTAS scale works in different subgroups in the same way. In other words, it is extremely important to determine whether the measurement tool provides biased group results using the measurement invariance approach. Wicherts (2016) emphasized that measurement invariance is very important for the validity of tests. In the literature, we could not find any study about measurement invariance in the field of nanotechnology. Very few studies have been found in the literature on measurement instruments used in hard sciences. Some of them are given below.

Rocabado et al. (2019) performed measurement invariance testing for the configural, metric, and scalar models comparing black female students and all other students within the traditional and flipped courses for the two-factor model prescribed for the pre and posttests. Their analysis results showed that configural, metric, and scalar invariance was ensured. Maier et al. (2013) developed a preschool teachers' attitudes and beliefs toward science teaching scale. They used teacher ethnicity, education level, and experience level as subgroups. They conclude that the three factors remained invariant across each subgroup. Luo et al. (2019) presented validity evidence of scores produced from the S-STEM measurement tool, and they concluded that measurement invariance results showed that the instrument items in the surveys measured the same constructs in the same ways across gender, age groups, and races/ethnicities. Braeken and Blömeke (2016) investigated the measurement equivalence of teachers' beliefs across countries for the case of 'mathematics as-a fixed-ability'. They concluded that data provided configural and metric invariance but did not provide scaler invariance across countries. Clearly none of the measurement invariance studies cited provide indisputable explanation about the steps of invariance measurement. It is obvious that there is a deficiency in the hard science literature in terms of emphasizing the importance of measurement invariance and elaborating step by step instructions and guidance.

Having examined the measurement model invariance with respect to configural, measurement weight, and structural covariance invariance for three groups of branches, three group of school types and two groups of genders, the present study arrived at the conclusion that configural, measurement weight and structural covariance invariances were ensured for branches, school types and genders. Also, residual invariance was ensured for genders. Residual invariances are not provided for branches, and school types leading us to conclude that not every item can be considered equally reliable across those groups.

In conclusion, the results of this study provide evidence that the measurement invariance requirement for valid group comparisons for the Nanoscience and Nanotechnology Awareness Scale has been satisfied; measurement invariance can be successfully implemented in science and technology education. Casas and Blanco-Blanco (2017) acknowledged using the method for Social Cognitive Career Theory (SCCT) models in predicting mathematical/scientific interests and occupational aspirations among Colombian secondary students. Another successful application was by Caputo (2017) in science and mathematics education of 7th grade secondary students in Italy. The Measure of Acceptance of the Theory of Evolution (MATE, a single-factor instrument that assesses an individual's overall acceptance of evolutionary theory) was tested to assess how it operates differently when administered to a population of non-science major preservice elementary teachers when compared with the reference population of in-service high school biology teachers and found to be reliable with the measurement invariance approach (Wagler & Wagler, 2013). As a result, it has been proved that the NSTAS scale will not generate biased measurements in comparing groups by teacher branches, school types and gender. Since the internal structure of NSTAS holds for different groups, NSTAS scale can be safely used to compare branch, school type and gender groups. Testing and interpreting the measurement invariance with the covariance structure approach using IBM AMOS-24, implemented with cases in this study, can be applied to all scales aimed at comparing different groups.

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Declaration of Conflicting Interests and Ethics

The authors declare no conflict of interest. This research study complies with research publishing ethics. The scientific and legal responsibility for manuscripts published in IJATE belongs to the authors. Ethics Committee Number: 81576613/605/1955049 Gazi University, Ankara.

Authorship Contribution Statement

Şeref Tan: Conceptualization, Data Analysis, Methodology, Software, Resources, Discussion, Writing, Supervision and Validation. **Zeki Ipek:** Investigation, Methodology, Resources, Writing. **Ali Derya Atik:** Conceptualization, Investigation, Data Analysis, Resources, Discussion, Writing. **Figen Erkoc:** Investigation, Data Analysis, Resources, Discussion, Writing, Supervision and Validation.

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6. APPENDIX

Table A1. Nanotechnology Awareness Instrument (Dyehouse et al., 2008)

For the following items, please indicate the extent to which you agree or disagree using the following scale: Strongly disagree, disagree, neutral, agree, or strongly agree.	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
What is your awareness of nanotechnology? I can:					
1. Name a nanoscale-sized object.					
2. Describe one way nanotechnology directly impacts my life.					
3. Name a field of study that currently conducts nanotechnology research.					
4. Describe one way nanotechnology may benefit society/humankind.					
5. Name an application of nanotechnology.					
6. Describe a process to manufacture objects at the nanoscale.					
7. Name an instrument used to make measurements at the nanoscale.					
8. Describe one way nanotechnology may directly impact my life in the future.					

For the following items, please indicate the extent to which you have participated in each activity using the following scale: Not at all/never, very little, sometimes/ occasionally, a fair amount, or a great deal.	Not at all/never	Very little	Sometimes/ occasionally	A fair amount	A great deal
What is your exposure to nanotechnology? I have:					
1. Heard the term nanotechnology.					
2. Read [something] about nanotechnology.					
3. Watched a program about nanotechnology.					
4. Had one [or more] instructors/teachers talk about nanotechnology in class.					
5. Participated in an activity involving nanotechnology [lab, project,…].					
6. Taken a class about nanotechnology.					

Table A2. Nanoscience and Nanotechnology Awareness Scale (NSTAS) - Turkish Version.

Farkındalık Alt Ölçeği (Awareness Subscale)	Kesinlikle Katılmıyorum	Katılmıyorum	Kararsızım	Katılıyorum	Kesinlikle Katılıyorum
1. Nanoölçek boyutunda bir nesne adı söyleyebilirim.					
2. Nanoteknolojinin hayatımı doğrudan etkileyen bir yöntemini söyleyebilirim.					
3. Bugünlerde nanoteknoloji araştırması yürüten bir çalışma alanı ismi söyleyebilirim.					
4. Nanoteknolojinin topluma/insanlığa faydalı olabilecek bir yöntemini tanımlayabilirim.					
5. Bir nanoteknoloji uygulamasının adını söyleyebilirim.					
6. Nanoölçekte nesneler üretmek için kullanılan bir yöntemi tanımlayabilirim.					
7. Nanoölçekte ölçüm yapmakta kullanılan bir araç ismi söyleyebilirim.					
8. Gelecekte nanoteknolojinin hayatımı doğrudan etkileyebilecek bir yöntemini söyleyebilirim.					

Deneyim (etkileşim) Alt Ölçeği (Exposure Subscale)	Hiçbir zaman	Nadiren	Ara sıra	Çok sık	Her zaman
7. Nanoteknoloji terimini duydum.					
8. Nanoteknoloji hakkında bir şeyler okudum.					
9. Nanoteknoloji hakkında bir program izledim.					
10. Sınıfta bir (veya daha fazla) öğretmen/öğretim elemanının nanoteknoloji hakkındaki konuşmalarını dinledim.					
11. Nanoteknoloji konusunun işlendiği bir etkinliğe katıldım (laboratuvar çalışması, proje, seminer, konferans).					
12. Nanoteknoloji hakkında bir ders aldım.					