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Measurement Invariance of the Digital Natives Assessment Scale Across Gender in a Sample of Turkish University Students

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Abstract

With reference to the digital natives' debate, there is a gap on digital natives' characteristics. To fill this gap, the Digital Natives Assessment Scale was developed to measure students' assessment of the degree to which they perceived themselves to possess the attributes of digital natives. The scale was developed within the Turkish language and requires further validation in cross-cultural adaptation processes. Moreover, to ensure scale validity, empirical investigation to test for invariance across different subgroups is required to engender confidence in the generalizability of the measure. This study aimed to provide initial validation of the Turkish Digital Natives Assessment Scale as a current measure for preservice teachers and to examine scale invariance across gender given that gender has been identified as an important contextual factor when studying digital natives' characteristics and use of digital technology. Confirmatory factor analyses and measurement invariance analyses across gender for cross-validation were performed. The confirmatory factor

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analysis results showed that a four-factor structure was confirmed for female and male preservice teachers together and female and male preservice teachers separately. In relation to measurement invariance, the results of the current study indicated support for configural invariance, metric invariance, and scalar invariance by gender.

Keywords
digital natives, gender, measurement invariance, preservice teachers

Introduction

Prior literature used different definitions for defining the new generation of technology users, namely Net Generation (Tapscott, 1998); Millennials (Oblinger, 2003); Screenagers (Rushkof, 2006); and the most popular, Digital Natives (Prensky, 2001). However, a common thread in all these terms is that the new generation differ than the old. Prensky (2001) emphasizes that the new generation spend their whole lives surrounded by and using computers, tablets, video games, smart phones, and all the other toys and tools of the digital age. It is claimed that living in a digital habitat or nature has affected digital natives' technology usage skills and that they have readily adopted new skills. For instance, according to Jones, Ramanau, Cross, and Healing (2010), these digital natives have grown up with computers and the Internet and are said to have a natural aptitude with high skill levels when using new technologies (Jones et al., 2010). In addition, digital natives are active experiential learners who like receiving instant information and are multitaskers and parallel processors who prefer graphics before text (Ng, 2012). Similarly, Johri, Teo, Lo, Dufour, and Schram (2014), Prensky (2001), and Rosen (2010) emphasize that digital natives have capability and preference for multitasking and application of graphics. However, there is no consensus on digital natives' repertoire of skills or characteristics. For instance, Thinyane's (2010) study showed that students who qualify for the digital native title (by their age) do not all use technology uniformly. Margaryan, Littlejohn, and Vojt's (2011) findings show that students (digital natives) use a limited range of established technologies. Kirschner and van Merrienboer (2013) also described digital natives as an urban legend. According to them, as learners, digital native students do not essentially know how to learn from new media, and they are not capable of working with, and controlling their own learning in multimedia and digitally pervasive environments. For that reason, in the literature, it is suggested that deeper research is necessary to elicit more sophisticated understanding of digital natives' attributes.

One of the studies designed to fill this gap is Teo's (2013a) work on the Digital Natives Assessment Scale (DNAS). Teo has developed a reliable and valid scale through relevant exploratory and confirmatory analyses. The scale has 21 items,

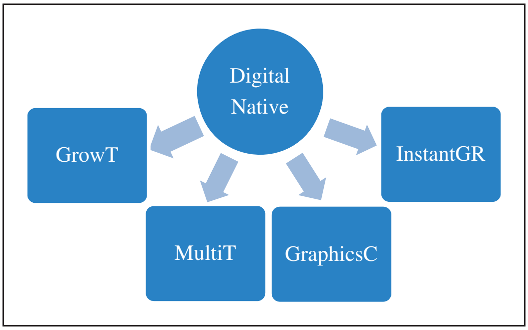

Figure 1. Digital nativity framework.
GrowT = grow up with technology; MultiT = comfortable with multitasking; GraphicsC = reliant on graphics for communication; InstantGR = thrive on instant gratifications and rewards.

with a 7-point Likert response format, ranging from 1 = *strongly disagree* to 7 = *strongly agree*. With this scale, Teo (2013b) offered a framework to classify a list of behaviors that have alluded to digital natives. Based on his framework (Figure 1), the DNAS has four factors: *Grow up with technology*, *Comfortable with multitasking*, *Reliant on graphics for communication*, and *Thrive on instant gratifications and rewards*.

In the Grow up with technology factor, it was emphasized that digital natives have been born in the digital age, with the possibility to use digital items at an earlier age. According to Rainie (2006), digital natives tend to use sophisticated technologies more frequently and at an earlier age to communicate and socialize than past generations. The Comfortable with multitasking factor refers to an act of attending simultaneously to two or more parallel tasks. Palfrey and Gasser (2013) stated that digital natives can put their ability to juggle tasks to work to make them more productive in high-stress jobs. Moreover, the Reliant on graphics for communication factor refers to exposure to a range of multimedia technologies from a young age and that digital natives display a preference for and a comfort in a graphics-rich rather than a text-only environment (Teo, 2013b). According to Cameron (2005), students desire graphic information with a text backup. In the last factor, Thrive on instant gratifications and rewards, digital natives crave interactivity and immediate response in their daily lives with reference to their digital devices.

Teo, Kabakci Yurdakul, and Ursavas (2014) adapted this scale into the Turkish language and culture. In the preliminary adaptation phases, items were subjected to the translation and back-translation processes, after having consensus on the Turkish DNAS items from four experts. Furthermore, the measure was pilot-tested with 32 preservice English language teachers. This along with the work of the experts facilitated face validity, and the administration of the test initially and then after 2 weeks to the preservice teachers secured acceptable test–retest validity for the items of the DNAS, with positive and statistically significant correlation coefficient ($r = .889$). Finally, confirmatory factor analysis (CFA) was conducted to confirm four fixed factors of DNAS with the participation of $N = 557$ preservice teachers. According to the analysis, the CFA model of Turkish DNAS was an acceptable fit ($\chi^2 = 673.539$; $\chi^2/df = 3.893$; Tucker–Lewis index = .90; comparative fit index (CFI) = .91; root mean standard error of approximation = .07 [.07, .09]; standardized root mean square residual = .068).

However, one of the key concerns on scale adaptation is measurement invariance, as there is a critical assumption that the scale is measuring the same trait in each group. Invariance would mean that for the groups being compared, the measure in question has the same measurement and scaling properties (Gomez & McLaren, 2015). While conducting this analysis, it is aimed to assess the equivalence of the measurement instrument across different respondent groups on a variety of measurement-related criteria including configural, metric, scalar invariance, factor loadings, mean and covariance of latent factors, item intercepts, and random measurement errors (Cheung, 2008; Cheung & Lau, 2012; Parameswaran, Kishore, & Li, 2015). In Teo's (2015) study, tests of measurement invariance revealed score equivalence among the students for each of the four factors of the Chinese DNAS. This study, however, focuses on measurement invariance by gender because gender differences on technology-related issues could be associated with digital nativity. For example, Padilla-Meléndez, Aguilo-Obra, and Garrido-Moreno's (2013) study provided evidence that gender differences are prevalent in the effect of playfulness in student attitudes toward technology and the intention to use it. According to Correa's (2015) study, men had significantly higher levels of digital skills (nine questions about people's knowledge of computer- and Internet-related terms) than women. Vekiri and Chronaki (2008) stated that boys have more positive computer self-efficacy and value beliefs than girls. Moreover, Mazman and Kocak-Usluel (2011) found that social network usage differs by gender. Tsai and Tsai's (2010) study showed that boys and girls used the Internet for significantly different purposes, suggesting that the Internet played different roles for boys and girls. Therefore, it is important to test construct validity and measurement invariance of a technology-related instrument across gender.

Cooper and Weaver (2003) observed that gender had marked an important part of differences in approaches to technology and that the gender divide had been sustained through computer anxiety. They concluded that girls and women had suffered more than boys and men. In comparing between the two decades (1990s and 2000s), Powell (2014) found that the gender gap digital divide appeared to be closing. The changing scene over the decades was also highlighted by Popovich, Gullekson, Morris, and Morse (2008) who found that gender was a significant predictor of computer anxiety in 1986 but not in 2005. However, Bozioneleos (2002) noted that the older studies had looked at computer anxiety but called for measures that embraced a positive approach to computers and technology and the Technology Acceptance Model (Teo et al., 2014) falls within these parameters.

Although Bunz, Curry, and Voon (2007) argued that the digital divide on gender had more to do with stereotyping and perception than reality, the fact remained that some careers persisted as male or female dominated. For example, fewer women traditionally opt for engineering than men (Kusku, Ozbilgin, & Ozkale, 2007). It is therefore important that a measure that encompasses a positive orientation toward computers, such as the Technology Acceptance Measure (Teo et al., 2014), elicits invariant responses across gender.

Purpose

The primary purpose of this study is to validate the DNAS as a current measure for preservice teachers across gender. A secondary purpose is to examine the measurement invariance of the instrument across gender because gender has been discussed as an important contextual factor when studying digital natives' characteristics and use of digital technology. The following research questions guide the study:

1. Is the DNAS factor structure different by gender?
2. Is the DNAS factor structure invariant by gender?

Method

Participants and Procedure

Participants ($N = 2024$) included 70.8% ($n = 1432$) female and 29.2% ($n = 592$) male preservice teachers from 14 different State universities in Turkey during the 2013–2014 academic year. The age of the participants ranged from 17 to 53 years with the mean at 20.77 years ($SD = 1.52$). Respondents had been using computers for a mean of 8.27 years ($SD = 2.81$) and the Internet for a mean of 6.82 ($SD = 2.54$) years. Four participants did not indicate their gender, and 17 participants provided unclear responses and so were excluded from the data analysis process. No course credits or rewards were given to the participants who volunteered in this study. Also, data were gathered during course hours with the permission of faculty staff. Scale response time was approximately 10 to 12 minutes and before the response participants were informed about the nature and content of the study. It was emphasized that responses would be used only in this research context, and their responses would be kept confidential.

Instrument

The Turkish version of the DNAS (Teo et al., 2014) includes 21 items covering four subscales of Grow up with technology (Five items: e.g., "I use the computer for leisure every day"); Comfortable with multitasking (Six items: e.g., "When

Table 1. Participants Gender Frequency, Means, Standard Deviations, Skewness, and Kurtosis Coefficients.

	M				*SD*				Skewness				Kurtosis			
	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4	F1	F2	F3	F4
Female	5.19	5.32	4.67	5.41	1.36	1.34	1.31	1.06	−0.62	−0.74	−0.37	−0.74	−0.40	−0.15	−0.44	0.50
Male	5.33	5.47	4.55	5.35	1.30	1.26	1.37	1.09	−0.86	−0.91	−0.36	−0.85	0.36	0.47	−0.45	0.67

Note. F1 = Grow; F2 = Multy; F3 = Graphic; F4 = Instant.

using the internet for my work, I am able to listen to music as well"); Reliant on graphics for communication (Five items: e.g., "I prefer to receive messages with graphics and icons"); Thrive on instant gratifications and rewards (Five items: e.g., "I expect quick access to information when I need it"). These 21 items were hypothesized to load on the previously mentioned four factors and were measured on a 7-point scale with 1 = *strongly disagree* and 7 = *strongly agree*. The scale revealed acceptable reliability for all constructs. The internal consistencies of the subscales are presented in Table 1, and descriptive statistics for the items are presented in Table 3.

Data Analysis

To explore the patterns in and test the quality of the data, descriptive statistics, means and standard deviations, and indictors of kurtosis were run. These were explored across gender and factor level, and the outcomes are presented in Table 1. Analysis of the data was performed using CFA. Because the DNAS is an established measure with a fixed factorial structure, CFA was not preceded by an exploratory factor analysis (Raykov & Marcoulides, 2010). Relevancy of the measurement model that was used in the study was tested by using the AMOS 21 program (IBM SPSS® Amos™ 21). In addition to this, univariate, multivariate normality, measurement model fit indices, convergent and discriminant validity, and measurement invariance analysis were calculated.

Results

Descriptive Statistics

Maximum-likelihood estimation, a parametric technique, was employed in parameter estimations. This technique requires the fulfillment of the multivariate normality assumption. In addition, each one of the variables observed for multivariate normality needs to have univariate normality. The data for all variables were normally distributed (i.e., skewness and kurtosis values) within Kline's

Table 2. Single-Group Confirmatory Factor Analysis.

	Values		
Fit indices	Female	Male	Criteria
χ^2	1131.28*	608.71*	p value must be nonsignificant
χ^2/df	6.66	3.58	<5
GFI	.92	.90	>.90
TLI	.92	.90	>.90
CFI	.93	.92	>.90
RMSEA	.06	.06	<.08

Note. GFI = goodness-of-fit index; TLI = Tucker–Lewis index; CFI = comparative fit index; RMSEA = root mean standard error of approximation.
*$p < .05$.

postulated criteria. The skewness and kurtosis values ranged, respectively, from−0.91 to −0.37 and −0.50 to 0.67. According to Kline's (2009), value of under |3.0| for skewness and value of under |10.0| for kurtosis indicate normal distribution. These values demonstrated univariate normality in the data for this study. For the multivariate normality, Mardia's normalized multivariate kurtosis value was calculated. Mardia's (1970) coefficient for the data in this study was 173.219, which is lower than the value of 483 computed based on the formula $p(p + p)$ where p equals the number of observed variables in the model (Raykov & Marcoulides, 2008). With this criterion, multivariate normality of the data in this study was fulfilled.

Test of the Measurement Model

The measurement model in this study was tested with CFA, using the computer software program AMOS 21. The researchers used a variety of fit indices for measurement model fit (Table 2.).

The χ^2 (chi-square) test assesses the fit of the model by comparing the sample correlation matrix with the correlation matrix estimated under the model. Small values indicate a good fit, reflecting a small discrepancy between the structure of the observed data and the hypothesized model. Because χ^2 has been found to be too sensitive to the sample size (Hu & Bentler, 1999), the ratio of χ^2 to its degrees of freedom χ^2/df (chi-squared/degrees of freedom) was used, and a range of not more than 3.0 is indicative of an acceptable fit (Gefen, Karahanna, & Straub, 2003; Kline, 2005). Root mean standard error of approximation reflects the extent to which the model fit approximates a reasonably fit model; the model fit is acceptable when values are less than .08 and good when values are less than .05 (McDonald & Ho, 2002). Goodness-of-fit index, Tucker–Lewis index, and CFI compare the hypothesized model to a *null* or worst fitting model, taking into account model complexity, and indicate an acceptable model fit when values are greater than .90, and a good model fit when values are greater than .95 (Hu & Bentler, 1999; Klem, 2000; McDonald & Ho, 2002).

Convergent Validity

Fornell and Larcker (1981) proposed a comprehensive testing model including three steps to get convergent validity for scale items. These steps are as follows:

1. The item reliability of every structure in the scale
2. Composite reliability (CR)
3. Average variance extracted (AVE)

First, item reliability is determined with the factor loading that includes items in the factor structure. The factor loading for all items exceeds the recommended level of .5, the level at which factor loadings are statistically acceptable and reliable (Hair, Black, Babin, & Anderson, 2010). Factor loadings range from .38 to .85 for females and .33 to .85 for males. After excluding item 11 and item 17, convergent validity for the proposed items and constructs in this study are adequate and acceptable. Second, the CR of each construct was calculated. Nunnally and Berstein (1994) stated that for CR, a value of .70 and higher is acceptable to be adequate. In this study, CR values range from .79 to .87 for each construct. For the final indicator of convergent validity, AVE was calculated. AVE was determined separately for each construct. According to Fornell and Larcker (1981), if the AVE equals or exceeds .50, it is judged to be adequate. In this study, AVE values ranged from .44 to .54 for all the groups. The acceptable reference and critical values for reliability and validity[a] were demonstrated in Table 3. The CR is computed by squaring the added factor loadings divided by the sum of the added factor loadings squared and total error variances $(\Sigma\lambda)^2/(\Sigma\lambda)^2 + (\Sigma\eta)$; AVE is computed by adding the squared factor loadings divided by the sum of the total factor loadings squared and total error variances, $(\Sigma\lambda^2)/(\Sigma\lambda^2) + (\Sigma\eta)$ (Hair et al., 2010). As given in Table 3, the AVE and CR met the recommended guidelines, indicating that the convergent validity for the proposed items and constructs in this study is adequate.

Discriminant Validity

Discriminant validity, also known as shared variance, is generally used for analyzing relationships between latent variables. Fornell and Larcker (1981) stated that discriminant validity is established if a latent variable accounts for more

Table 3. Results for the Measurement Model.

	Unstandardized coefficients (standardized)				Descriptive statistics			
					Female		Male	
	Female	Male	AVE (>.50)[a]	CR (>.70)[a]	*M*	*SD*	*M*	*SD*
F1			.53 (.49)	.85 (.82)				
Item1	1.09 (0.73)	1.16 (0.70)			5.32	1.90	5.54	1.81
Item2	0.88 (0.78)	1.05 (0.78)			5.74	1.44	5.82	1.47
Item3	0.70 (0.69)	0.89 (0.71)			5.99	1.31	5.87	1.37
Item4[b]	1.00 (0.66)	1.00 (0.60)			4.76	1.93	4.99	1.83
Item5	1.17 (0.76)	1.19 (0.68)			4.15	1.98	4.47	1.93
F2			.54 (.52)	.87 (.86)				
Item6	1.41 (0.79)	1.330 (0.78)			5.01	1.79	5.28	1.63
Item7	1.53 (0.84)	1.41 (0.81)			5.27	1.81	5.54	1.66
Item8	0.98 (0.67)	1.07 (0.72)			5.98	1.45	5.99	1.42
Item9	1.31 (0.77)	1.23 (0.72)			5.41	1.70	5.51	1.64
Item10	1.19 (0.81)	1.11 (0.77)			5.65	1.47	5.91	1.37
Item11[b]	1.00 (0.48)	1.00 (0.45)			4.61	2.07	4.63	2.13
F3			.52 (.50)	.84 (.82)				
Item12	0.60 (0.54)	0.60 (0.52)			4.03	1.70	4.03	1.80
Item13	0.99 (0.88)	0.96 (0.83)			4.75	1.68	4.69	1.76
Item14[b]	1.00 (0.87)	1.00 (0.85)			4.54	1.70	4.51	1.79
Item15	0.83 (0.69)	0.76 (0.63)			4.33	1.79	4.16	1.83
Item16	0.56 (0.54)	0.67 (0.60)			5.72	1.56	5.40	1.71
F4			.46 (.44)	.80 (.79)				
Item17	0.73 (0.38)	0.63 (0.33)			4.21	1.74	4.16	1.83
Item18	1.14 (0.78)	1.02 (0.73)			5.89	1.29	5.77	1.37
Item19	1.10 (0.65)	1.10 (0.66)			5.56	1.50	5.39	1.61
Item20	1.35 (0.74)	1.24 (0.75)			5.36	1.61	5.52	1.59
Item21[b]	1.00 (0.74)	1.00 (0.75)			6.05	1.19	5.94	1.27

Note. AVE = average variance extracted; CR = composite reliability.
[a]Indicates acceptable limit.
[b]This value was fixed at 1.00 for model identification purposes.

variance in its associated indicator variables than it shares with other constructs in the same model. If discriminant validity is not established, then conclusions made regarding relationships between constructs under investigation may be incorrect (Farrell, 2009). To assess for discriminant validity, the square root

Table 4. Discriminant Validity for the Measurement Model.

	Construct	Grow	Multy	Graphic	Instant
Female	Grow	(0.728)			
	Multy	0.634**	(0.734)		
	Graphic	0.375**	0.476**	(0.721)	
	Instant	0.464**	0.510**	0.452**	(0.678)
Male	Grow	(0.700)			
	Multy	0.642**	(0.721)		
	Graphic	0.476**	0.506**	(0.707)	
	Instant	0.578**	0.575**	0.485**	(0.663)

**$p < .001$.

of the AVE for a given construct was compared with the correlations between that construct and all other constructs (Teo, 2009). The correlation values for each construct and AVE values are demonstrated in Table 4. In the matrix, the elements located on the diagonal and specified within parenthesis present the square root of AVE for each construct. Off-diagonal elements in the matrix present correlations between constructs. To achieve discriminant validity, diagonal elements of the matrix should be greater than corresponding off-diagonal elements (correlation between constructs; Fornell & Larcker, 1981). As presented in Table 4, discriminant validity appears satisfactory at the construct level in the case of all constructs.

Invariance Analysis

Multigroup measurement invariance analyses were performed using maximum likelihood and based on variance–covariance matrix via AMOS 21. Measurement invariance was conducted in four steps according to Byrne's (2010) recommendations. She suggested (a) configural, (b) metric, (c) scalar, and (d) strict invariance. In measurement invariance studies, invariance of the models by groups is calculated through $\Delta\chi^2$ and ΔCFI values. According to Byrne (2010), if the χ^2 is statistically significant, it indicates that measurement invariance is not obtained. However, the use of $\Delta\chi^2$ has been criticized because of its sensitivity to sample size (Cheung & Rensvold, 2002). Moreover, they recommended the use of CFI (ΔCFI) to avoid problems of this nature. In addition, they emphasized that with ΔCFI absolute values smaller than .01, invariance conditions for the groups are obtained. According to Brown (2006) and Schmitt and Kuljanin (2008), having the first three types of invariance model fit (configural, metric, and scalar) is adequate to test data instruments' measurement invariance.

Table 5. Measurement Invariance Tests for DNAS Scale Across Gender.

	χ^2	*df*	CFI	$\Delta\chi^2$	Δdf	ΔCFI	*p*	Result
M1: Configural invariance (Baseline)	1740.095	340	.933	–	–	–	.000	Accept
M2: Metric invariance (Invariant Λ)	1768.475	357	.933	28.381	17	.000	.041	Accept
M3: Scalar invariance (Invariant Λ, τ)	1808.990	367	.931	40.515	10	.002	.000	Accept
M4: Strict invariance (Invariant Λ, τ, Θ)	1898.087	401	.929	89.097	34	.002	.000	Accept

Note. Baseline, noninvariance model; Λ = loading; τ = threshold; Θ = residual variances; M = model; DNAS = Digital Natives Assessment Scale; CFI = comparative fit index.

Configural invariance. Configural invariance refers to factor structure equivalence between samples (Hair et al., 2010). In other words, both of the groups have the same number of constructs and items associated with each construct (Campbell, Barry, Joe, & Finney, 2008). According to construct validity results (Model 1), the constructs are congeneric across groups (female–male). As can be seen in Table 5 (Model 1), the fit of the model data was acceptable. This result indicates that configural invariance of this scale is established.

Metric invariance. Metric invariance establishes the equivalence of the basic *meaning* of the construct because the loadings denote the relationship between indicators and the latent construct (Hair et al., 2010). Metric invariance test determines cross-group validity beyond the basic factor structure. Also, this is a critical step for measurement invariance (Jöreskog & Sörbom, 1999). In this step, χ^2, *df*, and CFI values were calculated. For the metric invariance, Model 2 was compared with Model 1, and $\Delta\chi^2$, Δdf, and ΔCFI values were interpreted. $\Delta\chi^2 = 28.381$ was significant at $\alpha = .05$ level, and $\Delta\text{CFI} = .000$ value was smaller than .01. As shown in Table 5 (M2), the ΔCFI (=.000) was not large enough to reject metric invariance, and this is therefore indicative of metric invariance.

Scalar invariance. Another essential invariance type for comparisons of groups is scalar (strong) invariance (Meredith, 1993). Scalar invariance type is important to make meaningful comparisons between groups or different samples. In addition to the invariance of the factor structure and invariance of the factor loadings, each structure of the observed variable is tested with the invariance of the calculated regression constant. To test scalar invariance, Model 3 and Model 2 were compared. As it is demonstrated in Table 5, the $\Delta\chi^2 = 40.515$ value was statistically significant at $\alpha = .05$ level. However, ΔCFI was smaller than .01 and thus indicates that scalar invariance was obtained.

Strict invariance. Finally, for the measurement invariance, Model 4 was tested across Model 3 to obtain strict invariance. According to Model 4, the $\Delta\chi^2$ value was statistically significant at $\alpha = .05$ level. Again, the ΔCFI value was smaller than .01 and provided empirical support for scalar invariance.

Discussion

This study aimed to test validation of the DNAS that was developed by Teo (2013b) and adapted into Turkish by Teo et al. (2014) and to examine the measurement invariance of the instrument across gender. The main purpose was to verify the dimensional structure of the four factors: Grow, Multy, Graphic, and Instant with CFA and test measurement invariance across gender. From the data obtained with samples of preservice teachers from Turkey, the results showed first that, at the CFA level, there was support for the four-factor hypothesized model that adapted version of DNAS. Overall, the four-factor model was supported for combined preservice teachers and for female and male preservice teachers separately. Multigroup confirmatory factor analysis (MCFA) is a popular method for the examination of measurement invariance and specifically, factor invariance (French & Finch, 2008). The findings from the MCFA for invariance across male and female preservice teachers showed good fit for the configural model. Also, there was no difference between the configural model and the metric invariance model; the metric invariance model and the scalar invariance model; and the scalar invariance model and the strict invariance model.

The findings from the MCFA also showed no difference in mean scores for all four latent factors (Grow, Multy, Graphic, and Instant). In relation to measurement invariance, the results of the current study indicated support for configural invariance (pattern structure), metric invariance (factor loadings), and scalar invariance (item intercepts) by gender.

In the construction and validation of new scales, it is expected that several indicators of validity and reliability should be demonstrated in the early stages of the work (Loewenthal, 1996), and sound psychometric properties engender confidence in the continued use of the measure. Convergent and discriminant validity, demonstrated in this study, are numbered among the prominent indicators of validity for sound psychometric measures (Furr & Bacharach, 2008). Validity indicators are especially important, as the use of the measure extends across groups and cultures (Byrne, 2010). The present study therefore contributes to the extended use of Teo's (2013a) DNAS measure by demonstrating its invariance across gender. It was important to demonstrate gender invariance if the measure is to be extended cross-culturally given that gender differences in attitudes and approaches to technology is a topic of ongoing interest. The use of technology is an important part of the pathway to career progression in many professional occupations and a measure that can demonstrate gender invariance will therefore generate confidence in its application.

The issue of gender in assessing attitudes and approaches to technology has been one of preoccupation with researchers for several decades (Powell, 2014). According to Smith and Oosthuizen (2006), the differences between the sexes had been erased as a result of the focus on supporting women in enrolling for science subjects. However, attention had been focused on the reduction of fear and anxiety for both sexes leading Bozioneleos (2002) to call for concentration of attention on positive approaches to technology. It is important to bridge the digital divide not only in approaches to technology per se but also in respect to women accessing professions that were traditionally seen as male dominated such as engineering (Kusku et al., 2007). If the perception that fewer women than men are scientifically orientated (Tsai, Lin, & Tsai, 2001) is to continue to be changed, then the role of positive measures such as the Technology Acceptance Measure can serve to facilitate this process by demonstrating invariance across gender. Results from the present study have shown that although there are clear individual differences within each group as shown by the variances in both males and females, there are similarities across the two groups as shown by the four invariance tests presented within the results. Three of these invariance tests (configural, metric, and scalar) are consonant with Brown (2006) and Schmitt and Kuljanin's (2008) recommendation of test of adequacy for measurement invariance. When tested across gender, women and men do not respond differentially to the Technology Acceptance Measure, and this is important because gender ratios typically approximate 50:50 across populations.

Several limitations exist in this study. Although the Turkish DNAS has a good model fit, it is possible that other constructs could be considered to enhance our understanding preservice teachers' digital nativity. Future research could include more tests of measurement invariance across samples (technical or social discipline) and populations (Eastern or Western culture) of the measure in response to increasing complexity in the diffusion of innovation and rapid changes in the technology, with a view to achieving greater precision in measurement and validity. Second, the use of self-reported data in this study could be susceptible to common method variance, leading to inflation in the relationships among constructs and, subsequently, measurement bias. Third, although the forms of validity established in the present study are invaluable, other forms of validity would augment the quality of the findings reported here. One that is prominent among the range of validities is predictive validity (Loewenthal, 1996), and future studies could look at objective behavioral outcome measures that are linked to the DNAS and that capture the efficiency and effectiveness of technological use.

In Margaryan et al.'s (2011) research, the findings show that technical discipline (engineering) students used more technology tools when compared with students of a nontechnical discipline (social work) and were also more digitally native than them. Future studies could examine these kinds of differences between groups, to ascertain whether participant groups with less technological training or predisposition endorse items and factors in the systematic pattern that was evident in the present study. Teo (2013a) suggests that future studies could include other variables that may influence DNAS's factorial validity. To ensure that the DNAS is usable and valid for different subgroups, tests of measurement invariance should be performed across subgroups including departments, specific disciplines, school levels (primary, secondary, college, etc.), across culture, and socioeconomic status groupings and having different kind of technological items to cover the range of usage in diverse learning environments.

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