Using Confirmatory Factor Analysis and Model Respecification to Reproduce a One-Factor Model of the PSVT: R

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Abstract

The Purdue Spatial Visualization Test: Visualization of Rotations (PVST: R) is a widely used assessment of spatial ability. This paper investigated the factor structure of the PSVT: R through confirmatory factor analysis with data from 335 engineering design graphics students enrolled in an introductory course. A hypothesized one-factor model and alternative models were examined.

Introduction

This research is an extension of (Ernst, Williams, Clark & Kelly, 2016). exploratory factor analysis of the PSVT: R. The researchers found that data from engineering design graphics students was not favorable to a robust one factor solution and that the data could conceivably support a wide variety of solutions from one to three factors. This suggested that not all of the items were indispensable for the one-factor construct that the test asserts to measure. This study employed the structural equation modeling (SEM) technique of confirmatory factor analysis to examine the unidimensionality of the PSVT: R through the examination of a hypothesized one-factor model with all 30 test items. In addition, model respecification was employed to determine if there were alternative one-factor models using fewer PSVT: R items that might provide a better model-fit.

Methods

Participants

The participants were 335 students enrolled in introductory engineering design graphics classes. The participants were predominately male (79.1%) and White (75.2%). The majority of the participants (88%) were between 18-21 years old. The mean grade point average for the group was 3.31 (*SD* = .51).

Procedures

Data were analyzed using SPSS 24 and AMOS 7.0. A hypothesized one-factor model where the 30 PSVT: R items formed one factor and three additional one-factor models were examined. In this study the goodness-of-fit of the proposed models was examined with model-fit indices that are prevalent in the literature. We examined the likelihood-ratio chi-square statistic (χ^2), the root mean square error of approximation (RMSEA; Browne & Cudeck, 1993), the standardized root mean square residual (SRMR), the Tucker Lewis index (TLI: Tucker & Lewis, 1973) and the comparative fit index (CFI; Bentler, 1990).

Nonsignificant chi-square probability values larger than the .05 level are deemed acceptable. Values of less than .05 for the RMSEA are generally accepted and values as high as .08 can be considered as reasonable (Browne & Cudeck, 1993; Kline, 2011). Accepted values for the SRMR range from .05 or less (Byrne, 2010) to .08 or less (Hu & Bentler, 1999). Accepted values for the TLI and CFI vary from .90 or higher (Bentler & Bonett, 1980) to .95 or higher (Byrne, 2010; Hu & Bentler, 1999; Kline, 2011) to .97 or greater (Schermelleh-Engel, Moosbrugger, & Muller, 2003). For the purposes of this study, any value above .90 was deemed acceptable.

Results

Table 1 illustrates the model-fit indices for all tested models as well as the fit indices from Maeda and Yoon (2011) and Maeda, Yoon, Kim-Kang, and Imbrie (2013). In the hypothesized one-factor model, all pathways in the model were statistically significant at the $p < .05$ level. However, the data did not produce acceptable levels of model-fit across all of the fit indices. The SRMR and RMSEA values fell within the acceptable range, while the TLI and CFI values were not acceptable. These finding were in contrast to two other studies which supported a one-factor model across all fit indices with the exception of the chi-square statistic (Maeda & Yoon, 2011; Maeda Yoon, Kim-Kang, & Imbrie, 2013).

Because of the discrepancy, the researchers used modification indices provided by AMOS to respecify the model in an attempt to fit the data to the hypothesized model. The modification indices indicated that 23 error terms should be correlated. Once correlated, the data for the respecified model produced measures of model-fit that were deemed acceptable across all fit indices with the exception of the chi-square statistic. All pathways in the model were statistically significant at the $p < .05$ level. While these results were similar to Maeda and Yoon (2011) and Maeda et al. (2013), the analysis violated the *a priori* model specification assumptions for SEM and lacked the theoretical justification for correlating the error terms (Hermida, 2015).

In addition, data for some variables were highly skewed and not normally distributed. Normality of data is a basic assumption for SEM analysis (Byrne, 2010). Because many of the items were skewed, additional one-factor models were examined that eliminated items with high skew scores. A 15 item one-factor model that eliminated scores with a skew value of two or higher yielded acceptable model-fit across all the fit indices with the exception of the chi-square statistic. In this model all pathways were statistically significant at the $p < .05$ level. A 10 item one-factor model in which all items with a skew value higher than 1.5 were eliminated yielding acceptable model-fit across all indices including the chi-square statistic. All pathways in the model were statistically significant at the $p < .05$ level.

Table 1. Model fit indices.

Factor Model	*df*	χ^2	*p*	RSMEA	SRMR	CFI	TLI
Models in Literature							
Maeda & Yoon (2011) One Factor Model 30 Items	405	670.01	<. .001	.033	**	.924	.918
Maeda, Yoon, Kim-Kang, & Imbrie (2013) One Factor Model 30 Items	405	1623.06	< .001	.035	**	.928	.923
Models Examined							
Model 1.Hypothesized One Factor 30 Items	405	866.42	.000	.058 (.053-.064)	.065	.656	.630
Model 2. One Factor 30 Items with Error Terms Correlated	382	444.74	.015	.022 (.011-.031)	.047	.953	.947
Model 3. One Factor 15 Items	90	126.84	.006	.035 (.019-.048)	.046	.928	.916
Model 4 One Factor 10 Items	35	44.50	.130	.029 (.000-.051)	.039	.963	.971

Note. ** Not reported; RMSEA = Root Mean Square Error of Approximation with 90% confidence interval in parentheses; SRMR = Standardized Root Mean Square Residual; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index

Conclusions

The hypothesized one-factor model did not produce an acceptable level of model fit across all the model-fit indices. Modifications to the hypothesized model based on AMOS modification indices produced a model that met all model-fit criterion with the exception of the chi-square statistic. However, the formulation of this model involved the correlation of 23 error terms without theoretical justification which can be problematic in SEM (Hermida, 2015). The researchers deemed this model unacceptable due to the extreme number of pathway modifications.

Another confounding issue was the non-normal distribution of some item scores. Some of the data were skewed. Since SEM relies on normally distributed data, these items were systemically eliminated in two additional one-factor models: a 15 item one-factor model contained items with skew less than 2 and the 10 item one-factor model contained items with skew less than 1.5. In the 10 item model all model-fit indices were acceptable. This finding suggested that a PSVT: R with fewer items can achieve a one-factor structure with data from engineering design graphics students and that is statistically significantly correlated with grade point average (p = .03).

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