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Confirmatory Factor Analyses of the PSVT: R with Data from Engineering Design Graphics Students

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Abstract

The Purdue Spatial Visualization Test: Visualization of Rotations (PSVT: R) is a widely used assessment of spatial ability. In this report, the factor structure of the PSVT: R test items was examined through confirmatory factor analysis with data from 541 engineering design graphics students. Stata 15 and Mplus 8.2 statistical software were used to examine a hypothesized 30 item one-factor model. Upon initial examination, data from engineering design graphics students produced a poor model-fit for the hypothesized one-factor 30 item model in both statistical programs. Respecified one-factor models with 10 test items and eight test items produced acceptable model-fit for the data employing Stata 15 and Mplus 8.2, respectively.

Introduction

Guilford and Zimmerman (1948) identified spatial visualization as a process of imagining movements, transformations, or other changes in visual objects. Spatial visualization, as one of the categories of spatial ability, McGee (1979) defined this term as the ability to mentally rotate, twist, or invert pictorially presented visual stimuli. The development of students' visualization skills has been a priority for engineering graphics educators for many years. Three-dimensional modeling programs require students to be able to manipulate objects and workplanes in 3D space (Wiebe, Branoff, & Hartman, 2001). Mental rotation is the ability to rotate two or three-dimensional objects rapidly and accurately in the mind (Linn & Petersen, 1985).

The Purdue Spatial Visualization Tests: Visualization of Rotations (PSVT: R) is a cognitive measure of an individual's spatial ability, specifically, spatial visualization ability of three-dimensional (3-D) mental rotation (Guay, 1980). The PSVT: R (Gay, 1976) has been frequently used in the fields of science, technology, engineering, and mathematics (STEM); especially, in engineering education for more than three decades (Sorby 2001a, 2001b). Guay cautioned that if spatial tests are susceptible to being solved by more than one strategy and do not require mental manipulation of visual images, the spatial tests might not accurately assess genuine spatial ability. Under these circumstances, Guay introduced the PSVT: R as an appropriate measure of an individual's mental rotation ability, as it required the use of the holistic strategy to solve spatial problems, rather

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than the analytic strategy. Guay (1976) originally developed the Purdue Spatial Visualization Test (PSVT1), consisting of three different subtests entitled "Developments," "Rotations," and "Views," which contains a total of 36 items, 12 from each subtest. Each subtest of the PSVT also had an independent extended version of 30 items entitled the Purdue Spatial Visualization Tests: Visualization of Developments (PSVT: D), Visualization of Rotations (PSVT: R), and Visualization of Views (PSVT: V). Yue (2006, 2007, 2008) identified 10 figural errors on 7 of 30 items of the PSVT: R during a process to convert the paper-and-pencil based PSVT: R to a computer-based test for an experimental study. The revised version was generated by correcting errors and checking all items in the test with permission of Guay.

The PSVT: R has been one of the most popular tests in engineering education to measure students' spatial visualization ability of mental rotation (Contero, Naya, Company, Saorin, & Conesa, 2005; Field, 2007) because the PSVT: R is unique in that 3-D objects in the test have inclined, oblique, and curved surfaces, which are more demanding to visualize than simple surfaces consisting of cubes as used in other tests.

Instrument

The PSVT: R is a 20-minute test for individuals aged 13 or older used to measure spatial visualization ability in 3-D mental rotation (Guay, 1980). The PSVT: R has 2 practice items followed by 30 test items which consist of 13 symmetrical and 17 asymmetrical figures of 3-D objects, which are drawn in a 2-D isometric format. All the figures contain shapes of cubes or cylinders with varied truncated slots. The items are ordered to be progressively more difficult, based on the rotated angles and axes (Guay, 1980). In each item, respondents are shown a figure and its rotated figure for an example of rotation and asked to find another figure's match as rotated in the same way of the example. The five given choices are rotated in different directions and shown at different angles.

The PSVT: R can be used for a variety of purposes: to determine the relationship between spatial ability and academic performance in different fields, such as anatomy, mathematics, science, technology, and engineering (Black, 2005); to assess gender differences (e.g., Sorby, 2001a, 2001b); to identify the effects of intervention courses to increase students' spatial ability and academic performance (e.g., Sorby, 2000; Hamlin, Veurink, & Sorby, 2008). Sorby's (2001a) six-year, longitudinal study found that the PSVT: R had been successfully used to identify students who need a remedial training course to enhance their spatial ability. In the three decades since its development, its vital role as an assessment tool in educational settings is evident and use of the PSVT: R in STEM education seems to be consistent.

Research Background

This study employed confirmatory factor analysis to examine the unidimensionality of the PSVT: R through the examination of a hypothesized 30 item one-factor model with data from engineering design graphic students. To date, only two studies have examined data from engineering design graphic students for the PSVT: R. One was an exploratory factor analysis (EFA; Ernst, Williams, Clark, & Kelly, 2016). The second was a confirmatory factor analysis (CFA; Williams, Ernst, Clark, & Kelly, 2018). In the EFA the researchers found that data from engineering design graphics students was not favorable to a one-factor solution and that the data supported a wide variety of solutions from one to three factors. Based on item analysis, the researcher's proposed that the multiple factors generated with data for this group could be due to item difficulty factors. This suggested that not all of the items were needed for the one-factor construct that the PSVT: R asserted to measure with data from engineering design graphics students.

In Williams, Ernst, Clark, & Kelly (2018), a CFA employing AMOS 7.0 was used to examine a hypothesized one-factor model where the 30 PSVT:

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R items formed one factor. In this study, the data did not produce acceptable levels of model-fit consistently across the fit indices. These findings were in contrast to other studies (Maeda & Yoon, 2011; Maeda Yoon, Kim-Kang, & Imbrie, 2013) which supported a one-factor model across all fit indices with the exception of the chi-square statistic (see Table 1).

Because of the discrepancy in model-fit, the researchers used modification indices provided by AMOS 7 to respecify the model in an attempt to fit the data to the hypothesized model. The modification indices indicated that 23 of the 30 error terms needed to be correlated for a one-factor solution. Once the 23 items were correlated, the data for the respecified model produced measures of model-fit that were 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 the result was similar to Maeda and Yoon (2011) and Maeda et al. (2013), the analysis violated the a priori model specification assumption for SEM and it lacked theoretical justification for correlating the 23 error terms (Hermida, 2015).

The maximum likelihood method employed by AMOS 7 assumes multivariate normality among the observed variables and preliminary univariate diagnostics showed strong deviations from normality for many of the variables. As data for many of the items were highly skewed, the researchers respecified a one-factor model that eliminated items with high skew values. This resulted in a 10 item one-factor model that yielded acceptable model-fit across all indices including the chi-square statistic. All pathways in the model were statistically significant at the $p < .05$ level (see Table 1). Therefore, this the purpose of this

Table 1
Model-fit indices for one-factor PSVT-R models.

Factor Model	*df*	χ^2	*p*	RMSEA	SRMR	CFI	TLI
Models in Literature							
Maeda & Yoon (2011). One Factor 30 Items	405	670.01	< .001	.033	**	.924	.918
Maeda, Yoon, Kim-Kang, & Imbrie(2013). One Factor 30 Items	405	1623.06	< .001	.035	**	.928	.923
Williams, Ernst, Clark, & Kelly (2018). One Factor 30 Items	405	866.42	.000	.058 (.053-.064)	.065	.656	.630
Williams, Ernst, Clark, & Kelly (2018). One Factor 10 Items	35	44.50	.130	.029 (.000-.051)	.039	.963	.971
Models Examined							
One Factor 30 Items Mplus 8.2	405	613.39	.000	.031 (.026-.036)	.111	.897	.889
One Factor 30 Items Stata 15	405	925.35	.000	.049 (.044-.053)	.053	.735	.716
One Factor 8 Items Mplus 8.2	20	52.67	.000	.055 (.037-.073)	.142	.911	.880
One Factor 10 Items Stata 15	35	159.26	.000	.080 (.068-.094)	.046	.913	.900

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

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research is reanalyzed data from a larger sample engineering design graphic students using Mplus 8.2 which is designed for categorical data and through Stata 15 employing a tetrachoric correlation matrix which is suitable for categorical data.

Methods

Participants

The participants were 541 engineering design graphics students enrolled in introductory engineering design graphics classes who were administered the PSVT: R. The participants were predominately male (80.21%) and White (76.9%). The majority of the participants (88.9%) were between 18-21 years old. The mean grade point average for the group was 3.34 (*SD* = .48).

Procedures

A CFA was employed to test a hypothesized one-factor model with data for the 30 PSVT: R test items with Mplus 8.2 and Stata 15. A CFA with the robust weighted least squares estimators with delta parameterization was conducted using Mplus 8.2 (Muthén & Muthén, 1998-2017). A CFA was also conducted with Stata 15 employing the tetrachoric correlation matrix. Goodness-of-fit of the proposed models was examined with model-fit indices that are prevalent in the literature and supported by Mplus 8.2 and Stata 15. 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) were examined.

Nonsignificant chi-square probability values larger than the .05 level are generally deemed as acceptable. Values of less than .05 for the RMSEA are generally accepted while values as high as .08 can be considered 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 for the CFI was deemed acceptable.

Results

On the initial data submission in Mplus 8.2, the 30 item one-factor model produced model-fit for the RMSEA that was acceptable although the other fit indices were outside of the range of acceptable model-fit (see Table 1). However, there were two warning statements on the printout which stated, "WARNING: THE BIVARIATE TABLE OF V9 AND V1 HAS AN EMPTY CELL" and "WARNING: THE BIVARIATE TABLE OF V9 AND V5 HAS AN EMPTY CELL". According to Muthén and Muthén (1998-2017), when a bivariate table has an empty cell, this implies a correlation of one between the two variables. This means that the two items are not statistically distinguishable and both items should not be used in the analysis. In this case, data for the test item was removed from the model and the analysis was run again. This iterative process was completed until no further error warnings were received. This resulted in an eight item one-factor model.

In Stata 15, the 30 item one-factor model did not produce acceptable model-fit across 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 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). The 10 item one-factor model based on Williams, Ernst, Clark, & Kelly (2018) was specified and reanalyzed. In the 10 item model, the SRMR, CFI, and TLI were acceptable and the RSMEA was acceptable, although borderline. Table 1 illustrates the model-fit indices for the one-factor model, the respecified one-factor model after accounting for the Mplus 8.2 warn-

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ings, as well as, those from other CFA studies in the literature.

Conclusions

The hypothesized 30 item one-factor model did not produce an acceptable level of model-fit across the fit indices with data from engineering design graphics students when employing Mplus 8.2 and Stata 15. Modifications to the hypothesized model, based on Mplus 8.2 error warnings, produced a model that met most of the fit criterion with the exception of the chi-square statistic and TLI. Only eight of the 30 items were included in this model. The eight items that formed one factor with Mplus 8.2 were items 13, 20, 23, 24, 25, 26, 27, and 28. For Stata 15, the 10 items from Williams, Ernst, Clark, & Kelly (2018) produced acceptable levels of fit across all fit indices with the exception of the chi-square statistic. The 10 items that formed one factor with Stata 15 were items 13, 22, 23, 24, 25, 26, 27, 28, 29, and 30. (see Table 2).

A confounding issue was the non-normal distribution of many of the item scores with data from engineering design graphics students. Table 2 shows these items and the percentage of students answering the items correctly. Over half the test items were correctly identified by 80 percent or more of the 541 participants.

These findings suggested that a PSVT: R with fewer items can achieve an acceptable one-factor structure with data from engineering design graphics students and that many of the items might be redundant with this group. As this sample was engineer design graphics students, one would expect that they would have a certain familiarity to the material and would find many of the items easy. The data on the percentage of correct responses in Table 2 appeared to support this. This may also be true with other types of college majors that rely on visual spatial relations. However, we do not have the data to support this assertion. Likewise, other college majors may

Table 2
Item level statistics for percentage correct for engineering design graphics students and appropriate for Mplus 8.2 and Stata 15 one-factor models.

Item Number	Percentage correct	Mplus 8.2	Stata 15
1	95		
2	95		
3	92		
4	96		
5	94		
6	90		
7	95		
8	89		
9	96		
10	90		
11	90		
12	82		
13	77	Appropriate	Appropriate
14	91		
15	84		
16	87		
17	84		
18	89		
19	81		
20	79	Appropriate	
21	87		
22	73		Appropriate
23	80	Appropriate	Appropriate
24	80	Appropriate	Appropriate
25	78	Appropriate	Appropriate
26	74	Appropriate	Appropriate
27	73	Appropriate	Appropriate
28	76	Appropriate	Appropriate
29	63		Appropriate
30	38		Appropriate

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find the items more difficult. With engineering design graphs students and research employing them, a shorter version of the PSVT: R could be as efficacious as the full-length version; saving time and effort in administration.

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