Factor Analysis
2009 Internal Structure for Deep Learning
Validity - Construct validity

Does the second-order factor solution, as found using NSSE 2005 data (Nelson Laird, Shoup, & Kuh, 2005), fit the 2009 NSSE data?

Purpose

NSSE focuses on student engagement and participation in effective educational experiences, thus some of the items on the survey measure activities which indicate deep learning approaches. In 2005, Nelson Laird, Shoup and Kuh conducted a study that identified a second-order factor solution with three subscales for facets of deep learning. These included high-order learning (4 items), integrative learning (5 items), and reflective learning (3 items). These subscales were then combined into one larger scale called deep learning. The purpose of this study was to replicate their study using 2009 data to find out if this structure fits with more recent data.

Data

All 2009 randomly sampled students from participating U.S. institutions were included in this analysis. This included responses from 160,755 first-year and 175,936 senior students from 617 colleges and universities. Results of all analyses were weighted by gender, enrollment status, and institution size.

Methods

First, exploratory factor analysis was used (Principle Components), in order to explore the factor structure that would emerge from the data. This was done separately for first-year students and then for seniors. As has been done in the past with NSSE data (e.g., Kuh, 2001; Nelson Laird et al., 2005), an oblique rotation (Oblimin with Kaiser normalization) was used because factors of engagement are assumed to correlate with one another.

In the second stage, a confirmatory factor analysis was done using the LISEREL8.80 statistical software program based on the results from the exploratory factor analysis.

Results

The scales, subscales, and component items that were created by Nelson Laird et al. (2005) are presented in Table 1. The reliability scores for these subscales and scale were also included and all were .70 or higher.

Table 1. Deep Learning Scale, Subscales, and Component Items

Deep Learning (FY α = .85, SR α = .86)	
	Combination of 3 subscales listed below
Higher-Order Learning (FY α = ..82, SR α = .83)	
analyze	Analyzing the basic elements of an idea, experience, or theory, such as examining a particular case or situation in depth and considering its components
synthesz	Synthesizing and organizing ideas, information, or experiences into new, more complex interpretations and relationships
evaluate	Making judgments about the value of information, arguments, or methods, such as examining how others gathered and interpreted data and assessing the soundness of their conclusions
applying	Applying theories or concepts to practical problems or in new situations
Integrative Learning (FY α = .70, SR α = .71)	
integrat	Worked on a paper or project that required integrating ideas or information from various sources
divclass	Included diverse perspectives (different races, religions, genders, political beliefs, etc.) in class discussions or writing assignments
intideas	Put together ideas or concepts from different courses when completing assignments or during class discussions
facideas	Discussed ideas from your readings or classes with faculty members outside of class
oocideas	Discussed ideas from your readings or classes with others outside of class (students, family members, co-workers, etc.)
Reflective Learning (FY α = .80, SR α = .80)	
ownview	Examined the strengths and weaknesses of your own views on a topic or issue
othrview	Tried to better understand someone else's views by imagining how an issue looks from his or her perspective
chngview	Learned something that changed the way you understand an issue or concept

Using the common criteria of retaining factors of eigenvalues greater than 1, the exploratory factor analysis results suggest a three factor solution. The component items for these factors support the past structure. The three factors cumulatively explain nearly 60% of the variance in the 12 survey items for both the first-year and the senior models. The factor loadings were relatively strong and only one item cross loaded in the first-year model only. The component correlations also show that the three factors are moderately related (component correlations ranging from .36 to .50). This supports an the existence of a second-order model.

Table 2. NSSE 2009 Deep Learning Exploratory Factor Analysis

	First -Year			Senior		
Items	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3
Higher Order Learning						
synthesz	.84			.84		
analyze	.81			.81		
applying	.79			.80		
evaluate	.79			.79		
Reflective Learning						
othrview		.86			.87	
ownview		.84			.85	
chngview		.79			.79	
Integrative Learning						
integrat			.75			.86
divclass			.75			.74
intideas			.68			.68
facideas			.59			.59
oocideas		.52	.54			.58
Percent Variance Explained	**38.32**	**11.71**	**8.72**	**38.96**	**12.45**	**8.50**
	Component Correlations			*Component Correlations*		
Factor 1	1.00			1.00		
Factor 2	.40	1.00		.36	1.00	
Factor 3	.48	.44	1.00	.50	.44	1.00

As shown by Table 3, both the second-order model fit very well for both first year and senior students with nearly identical fit statistics (fit indices > .95 and RMSEA = .05).

Table 3. Summary of Fit Indices for Confirmatory Factor Analysis

Model	χ^2	*df*	NFI	NNFI	CFI	RMSEA
First-Year Student Model	18,038.91	51	.98	.98	.98	.047
Senior Model	22,467.21	51	.97	.96	.97	.050

Finally, table 4 presents the factor loading and reliability estimates from the confirmatory factor analysis. The items on the first-order factors load in a similar way to those found in the exploratory factor analysis results (table 4). The first-order factors then load highly on the second-order factor (factor loadings ranging from .66 to .99). Integrative learning is nearly perfectly predicted by the second order (nearly 1 for both the first-year and senior models). As suggested in Nelson Laird et al. (2005) this relationship "may indicate a particularly strong connection between integrative learning and deep learning or may be an artifact of the constraints placed on the disturbances of the other two factors" (p. 15).

Table 4. Standardized Factor Loading and Reliability Estimates

	First-Year Factor Loadings				FY	Senior Factor Loadings				Senior
Factor and Items	HL	IL	RL	DL	R^2	HL	IL	RL	DL	R^2
Higher Order Learning				**.72**	**.52**				**.71**	**.50**
analyze	.74				.55	.74				.55
synthesz	.79				.63	.81				.65
evaluate	.72				.51	.73				.53
applying	.69				.47	.70				.48
Integrative Learning				**.98**	**.96**				**.99**	**.99**
integrat		.54			.30		.58			.33
divclass		.59			.35		.58			.34
intideas		.63			.40		.63			.39
facideas		.50			.25		.53			.28
oocideas		.58			.33		.60			.36
Reflective Learning				**.71**	**.50**				**.66**	**.43**
othrview			.75		.56			.76		.58
ownview			.80		.65			.82		.67
chngview			.72		.51			.71		.51

Note: R2 refers to the amount of variance accounted for in a factor by a particular indicator and is a reliability estimate.

DL = Deep Learning; HL = Higher Order Learning; IL = Integrative Learning; RL = Reflective Learning

References

Kuh, G. D. (2001). Assessing What Really Matters to Student Learning: Inside the National Survey of Student Engagement. *Change, 33*(3), 10-17, 66.

Nelson Laird, T. F., Shoup, R., & Kuh, G. D. (May, 2008). Measuring deep approaches to learning using the National Survey of Student Engagement. Paper presented at the Annual Meeting of the Association for Institutional Research. Chicago, IL.
http://nsse.iub.edu/pdf/conference_presentations/2006/AIR2006DeepLearningFINAL.pdf