Analysis of Felder-Silverman Index of Learning Styles by a Data-driven Statistical Approach *

Silvia Rita Viola[1], Sabine Graf[2], Kinshuk[3], Tommaso Leo[1]

[1] *Dip. Ingegneria Informatica, Gestionale e dell' Automazione "Maurizio Panti", Universita' Politecnica delle Marche, Ancona, Italy*

[2] *Vienna University of Technology, Women's Postgraduate College for Internet Technologies, Vienna, Austria*

[3] *Athabasca University, School of Computing and Information Systems, Athabasca, Canada*

sr.viola@gmail.com, graf@wit.tuwien.ac.at, kinshuk@ieee.org, tommaso.leo@univpm.it

Abstract

In this paper a data driven analysis of Felder-Silverman Index of Learning Styles (ILS) is given.

Results, obtained by Multiple Correspondence Analysis and cross-validated by correlation analysis, show the consistent dependencies between some styles; some latent dimensions present in data, that are unexpected, are discussed.

Results are then compared with the ones given by literature concerning validity and reliability of ILS questionnaire.

Both the results and the comparisons show the effectiveness of data driven methods for patterns extraction even when unexpected dependencies are found and the importance of coherence and consistency of mathematical representation of data with respect to the methods selected for an effective, precise and accurate modeling.

1. Introduction

Research on adaptivity in E-Learning has explicitly pointed out the importance of the modeling of cognitive characteristics of learners inside E-Learning environments in order to allow a more effective learning. Inside these characteristics, learning styles are one of the most analyzed cognitive features.

Mainly in order to provide adaptivity, a lot of research work has been done on analyzing learners attending online courses, and drawing conclusions regarding their learning styles.

This work deals with the analysis of Felder-Silverman Index of Learning Styles (ILS) questionnaire. ILS is in fact a very common tool for learners' learning styles assessment in adaptive systems.

The comparison with results on statistical properties of ILS is provided and discussed, pointing out the importance of consistency and coherence of mathematical and statistical assumptions with respect to the characteristics of data.

2. Related works

There are several different learning style models presented in literature; however, Felder-Silverman Learning Styles Model (FSLSM) [4] is often used for providing adaptivity regarding learning styles in Electronic Learning Environments (ELEs) thanks to the detailed description of the different dimensions of the style of a learner given by the model and to the attention to the strength of preference.

In order to detect both the preference and the degree of preference of learners for each dimension, the Index of Learning Styles (ILS) has been developed by Felder and Soloman [5]. ILS is a 44 item questionnaire aimed at identifying the learning styles according to FSLSM. In ILS the preference for each pairwise coupled learning style dimension is expressed as an odd integer ranging [-11, +11], with steps of +/-2.

In literature the validity, reliability, and consistency of ILS questionnaire have been studied [6, 13, 18], although there is no full consensus on results.

* This research has been funded partly by the Austrian Federal Ministry for Education, Science, and Culture, and the European Social Fund (ESF) under grant 31.963/46-VII/9/2002.

In general, it has been noticed that questionnaires could not be reliable since given answers could not correspond to the real behavior the question aims to investigate, both intentionally and not intentionally [3]. Nevertheless, ILS is at the present time the only validated tool for Felder-Silverman learning styles detection since other approaches are experimental [7] and is also a very diffused instrument.

Data driven approaches (to be intended as fully data driven or hybrid ones) can provide some useful methods aimed at discovering unexpected latent knowledge and relationships inside educational data, and graphical exploratory analysis [16] is well known for the purpose. Such an approach has been experimented on ILS data, leading to the identification of representative characteristics of ILS model as well as to the detection of some unexpected relationships [8].

3. Materials and Methods

The Felder-Silverman learning style model [4] characterizes each learner according to four dimensions: *active (A)* learners learn by trying things out and working with others whereas *reflective (R)* learners learn by thinking things through and working alone. *Sensing (Sen)* learners like to learn concrete material and tend to be practical whereas *intuitive (I)* learners prefer to learn abstract material such as theories and their meanings and tend to be more innovative than sensing learners. *Visual (Vis)* learners remember best what they have seen whereas *verbal (Ver)* learners get more out of words, regardless whether they are spoken or written. *Sequential (Seq)* learners learn in linear steps and prefer to follow linear stepwise paths whereas *global (G)* learners learn in large leaps and are characterized as holistic.

According to this description, the ILS questionnaire proposes a list of items effective in identify the style of each learner.

The resulting index of preference for each dimension is expressed by an odd integer ranging [-11, +11] since 11 questions are posed for each of the four dimensions. For each question 2 possible answers are available, the one with value +1, the other with value -1. As an example, when answering a question with an active preference, the learner's score is incremented by +1 while for reflective preference the score is decreased by 1 (i.e. -1 is added).

More formally, the degree of preference for each pairwise coupled dimension is obtained, in the simple case in which all questions have been answered, as

$$i(DIM,q) = \sum_{q \in DIM+} q_i - \sum_{q \in DIM-} q_i \qquad (1)$$

where each i, *DIM={A/R, S/I, V/V, S/G}* indicates all dimensions of pairwise coupled styles whose set of indexes is given by $I = \{i_{A/R}, i_{S/I}, i_{V/V}, i_{S/G}\}$, the set of all questions for every dimension is given by $Q_{DIM} = \{q_1^{DIM}, ..., q_{11}^{DIM}\}$, each q_i indicates the contribution given by the *i*-th questions inside the eleven related to each *DIM* to preference detection, and $q_i \in DIM+$ if $q_i = +1$, $q_i \in DIM-$ if $q_i = -1$. Data are expressed on a binary scale; the outcomes are expressed on a ordinal scale in which only the dominant preference (i.e. the difference of the two sums of $i(DIM,q)$) is explicitly given.

For the analysis a dataset containing the ILS answers of 207 individuals collected at Vienna University of Technology (85 individuals) and at Massey University in New Zealand (122 individuals) was used. The ILS matrix obtained from the dataset. The matrix *M* contains then positive and negative values expressed according to a binary scale; moreover, the vector of indexes in which preferences are stored, $I = \{i_{A/R}, i_{S/I}, i_{V/V}, i_{S/G}\}$ is a four feature vector described before.

In order to make data consistent with the application of both classical correlation analysis, such as Pearson's coefficients and p values, and with multivariate analysis, data were then transformed in frequencies, i.e. on absolute scale, as follows.

For every question q_i, *Q*=44, 2 numerical variables, namely the two answers to each questions,

$$a_1 = 1 \text{ if } q_i = 1, 0 \text{ otherwise}$$

$$a_2 = 1 \text{ if } q_i = -1, 0 \text{ otherwise}$$

were obtained.

Let *A* be the 207 x 88 matrix containing in rows individuals and in columns the a_i, *i*=1,…,88.

Such a matrix, well known in multivariate statistics as complete disjunctive form of a matrix, represents the same information as the ILS matrix expressed in binary [0,1] interval.

Learners showing a preference for each of the eight styles, irrespective with the strength of preference, were selected and grouped (table 1).

More formally, all the students showing $i(DIM,q) > 0$ or $i(DIM,q) < 0$, for each *DIM* respectively were selected and grouped according to their preferences. Then the frequencies of answers to each of all 88 answers were counted and divided by the cardinality of each group of students.

	A	R	Sen	I	Vis	Ver	Seq	G
Fr	117	90	120	87	181	26	91	116
%	57	43	58	42	87	13	44	56

Table 1 – Absolute and relative frequencies of occurrence of each style, irrespective for the degree of preference

The matrix *S* was then composed having in rows the frequencies of answer of each of the 88 answers, and in columns the eight possible Felder-Silverman learning styles, i.e. the relative frequency of occurrence of a certain answer inside the set of learners classified as belonging to a certain style.

Then *S* was decomposed according to Multiple Correspondence Analysis (MCA, [9, 12]) algorithm, and the first two non trivial axes, i.e. the second and the third, were selected for low dimensional representation.

MCA is a well known multivariate technique for data dimensionality reduction and graphical exploration, especially for categorical data. MCA works performing the optimal projection of a matrix in rows and columns space simultaneously on few dimensions (usually two), looking at independence of each value according to chi square metric. In this study, the algorithm proposed by Greenacre [9] has been chosen.

Such an analysis aims at analyzing, coherently with statistical assumptions, the intersections of clusters of ILS questions occurrence between styles, and focuses not only on the number of shared scores, but rather on which items are shared.

For cross validation procedure Pearson's correlation coefficients and related *p* values of the matrix of relative frequencies per style were analyzed.

4. Results

MCA on the matrix *S* outcomes clearly show (fig.1) that:

a) two styles belonging to different ILS dimensions, namely active and visual and sequential and sensing, are highly correlated;

b) the remaining styles appear to be relatively independent to each others, even if belonging to the some ILS dimension.

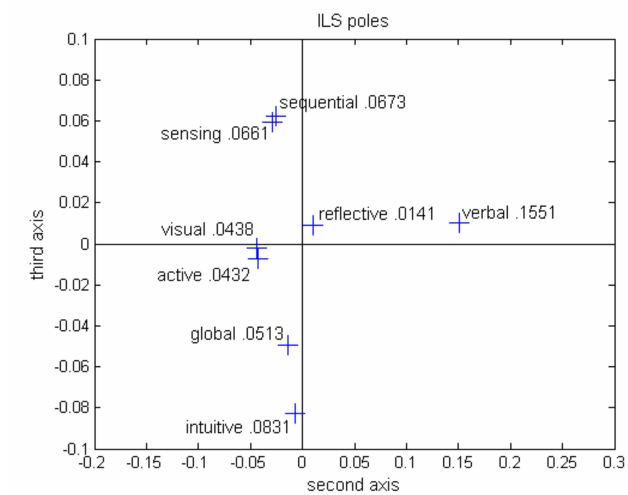

Figure 1 – MCA 2nd and 3rd axes in column space of *S*; the numbers near each label are the Euclidean distances from zero of each point

Pearson's correlation coefficients and related *p* values, given in table 2, shows that many dependencies between styles, in same cases also between styles belonging to the same ILS dimension (active/reflective .53, sequential/sensing .56, sensing/intuitive .43) are found.

These results could be motivated, in the setting of multivariate analysis, both by the contribution given to correlation by variables assessing different dimensions *DIM* and by the contribution given by variables assessing the dimension in analysis in the case of weak preference of a style, i.e. when *i(DIM,q)=+/-1* or *i(DIM, q)=+/-3*.

This also lead to hypothesize that some ILS dimensions assess two relatively independent latent variables rather than one variable having two opposite expressions.

Co	A	R	Sen	I	Vi	Ve	Seq	G
A	1	.53	.82	.72	**.92**	.03	.77	.84
R	*0*	1	.76	.62	.80	.25	.73	.73
Sen	*0*	*0*	1	.43	**.90**	.15	**.91**	.71
I	*0*	*0*	*0*	1	.77	.06	.47	.86
Vi	*0*	*0*	*0*	*0*	1	.02	.86	.89
Ve	*.77*	*.01*	*.15*	*.54*	*.87*	1	.10	.13
Seq	*0*	*0*	*0*	*0*	*0*	*.32*	1	.56
G	*0*	*0*	*0*	*0*	*0*	*.20*	*0*	1

Table 2 - Correlation coefficients of each style (upper triangular elements) and *p* values (lower triangular elements, in italic) of the matrix *S* in column space. In bold high (>.9) values

Table 3 shows the variables nearest to each style according to Euclidean distance in MCA plane.

As can be seen from table 3, some intersections within the styles exist. Most of the relevant answers for a sensing style are also relevant for a sequential style. The same applies for the intuitive and global style. These results show again the relation between the sensing/intuitive and sequential/global dimensions which is already mentioned in literature (e.g. [6]). From a cognitive point of view the reason might be seen in similar characteristics, for example both, sensing and sequential learners have a preference for details. Interesting at the proposed results is that most relevant answers for a sequential/global style are originally designed for the sensing/intuitive dimension. While most answers that are designed for the sensing/intuitive dimension are also relevant for the sequential/global dimension, only few answers designed for the sequential/global dimension are relevant for the sensing/intuitive dimension.

A	R	Sen	I	Vis	Ver	Seq	G
31a *.004*	28a *.004*	36a *.028*	38a *.048*	31a *.007*	31b *.089*	36a *.030*	38b *.022*
7a *.011*	37b *.005*	14a *.039*	6b *.055*	7a *.013*	11b *.104*	14a *.040*	44b *.027*
11a *.011*	25b *.005*	10a *.041*	18b *.055*	11a *.013*	7b *.105*	10a *.042*	22b *.028*
15a *.016*	40a *.006*	38a *.042*	44b *.058*	19a *.018*	19b *.107*	38a *.042*	18b *.029*
19a *.018*	30a *.006*	26a *.043*	22b *.058*	15a *.019*	3b *.115*	26a *.045*	30b *.030*
41a *.023*	33b *.007*	6a *.044*	36b *.061*	41a *.024*	27b *.115*	6a *.045*	6b *.030*
27a *.023*	41b *.009*	18a *.045*	2b *.062*	39a *.024*	23b *.118*	18a *.046*	20b *.032*
3a *.023*	17b *.009*	42a *.047*	10b *.062*	27a *.024*	43b *.120*	22a *.048*	2b *.032*
39a *.024*	4a *.010*	22a *.048*	20b *.063*	3a *.024*	1b *.123*	42a *.049*	10b *.034*
23a *.024*	15b *.010*	8a *.049*	30b *.064*	23a *.025*	39b *.124*	8a *.050*	14b *.037*

Table 3 – The nearest variables to each style vector according to Euclidean distance (in italic) in chi-square weighted optimal 2-dimensional MCA space

Moreover, intersections can be seen regarding the answers for an active and visual learning style. All of the relevant answers for an active style are also relevant for a visual style. Most of these answers are designed for the visual/verbal dimension. From a cognitive point of view this relation can be explained again from similar characteristics where, for example, active learners also prefer to learn from charts and diagrams rather from verbal text.

From statistical viewpoint, these results can be motivated looking at the behavior, that is variance and dependencies sensitive, of multivariate methods. In fact visual is the most populated group (table 1) and visual/active is the most high correlation, as well as high correlations, together with consistent variances, are achieved by sensing/sequential, and intuitive/global styles.

5. Discussion

In literature some contributions [6, 13, 18] provide an analysis of ILS questionnaire for what concerns internal consistency reliability, that is the extent to which a set of items can be considered as measuring a single latent variable, by using Cronbach's alpha coefficients [2], and validity, that is the extend to which a tool actually measures the latent variable that it is devoted at measuring, and inter-scale orthogonality by using Factor Analysis and Pearson's correlation coefficients.

Alpha	A/R	Sen/I	Vis/Ver	Seq/G	Size
[19]**	.595	.697	.633	.51	> 500
(6a)*	.56	.72	.76	.65	242
(6b)*	.62	.76	.69	.55	584
(6c)*	.51	.65	.56	.41	284
[13]	.60	.77	.74	.56	572
S 88 cols	.528	.631	.63	.427	207

Table 4 – Results for Cronbach's alpha coefficients. (6a)*, (6b)* and (6c)*, are respectively: Livesay's et al. results, Spurlin's results and Van Zwanenberg's results, and are reported in [6]; [19] considers only 4 poles scores, that is active, sensing, visual, sequential**

Results on Cronbach's alpha (table 4) achieved here are generally in agreement with the ones provided by literature; the alpha value for sequential/global, that is less than most other, is nevertheless shared with 6c study, whose results are drawn from a dataset more similar in size to the one used here.

However, it seems in general that alpha coefficients are not high, even if greater than the threshold .5, and this led to conclude for the co-existence of different latent dimensions underlying each ILS dimension that could not be peculiar to one dimension only. This hypothesis seems also to be confirmed when characterizing dimensions of ILS are searched [8].

Similar comparisons were performed for validity and inter-scale orthogonality, although these are of uncertain meaning for the different scales of data and procedures used.

For what concerns Pearson's correlation coefficients, that are shown in table 2, they are quite different from, and generally higher than, the ones given in literature.

However, these coefficients are said in all works except in [17] to be drawn from the analysis of scale scores, that are not expressed in absolute scale.

For this reason it can be hypothesized that the different results achieved here can be due to the sensitivity of Pearson's coefficients to the variance and the measurement scale of data. It is in fact known that for reliability of Pearson's coefficients, variables have to be expressed at least on interval scale [10].

In particular, in [6] and [17] correlations between sensing/intuitive and sequential/global dimensions (between .3 and .5) is attested; other correlations of uncertain strength are pointed out between active/reflective and visual/verbal (between .03 and .18), between active/reflective and sequential/global (between .01 and .18) and between visual/verbal and sensing/intuitive dimensions (between .03 and .11); the highest values are achieved in [17], where absolute scale id used.

Then the correlation of uncertain strength and meaning could be reasonably sustained from the strong correlation of only one pole of the ILS dimension.

For what concerns Factor Analysis, we will limit the comparison to orthogonal factors, since for Oblique Factors the assumption of orthogonality does not hold.

Factor loadings of ILS items are provided by [6], [13], and [17] even if different procedures are used in each of these studies.

In order to guarantee a minimal comparability with other results, Principal Component Analysis (PCA, [11]) was performed on ILS 44 items matrix *M* using Singular Value Decomposition (SVD). The matrix is full rank and all singular values have values greater than 1. If the eigenvalues of the covariance matrix are considered, 14 eigenvalues and related factors that satisfy the Kaiser criterion (eigenvalues greater than 1) are 14 with a cumulative percentage of variance of about 57%. This is in agreement with [6], [13], and [17].

However, if the loading of items on Right Singular Vectors are considered (table 5) it can be pointed out that the results are quite different from the ones given in literature.

While in fact in all works the number of questions highly represented by each factor, when provided, lead reasonably to conclude for the presence of some multivariate dependencies between styles, nevertheless the high loading clusters of items on each factors are different.

In both [13] and [17] absolute values of coefficients are generally higher and clusters of items belonging to sensing/intuitive dimension load high on the first factor in both studies, while on other factors clusters and high loading dimensions are different from each other.

Moreover, little information is given about the relative directions of coefficients with respect to zero.

While the high loading of clusters of visual/verbal dimensions in table 5 can be motivated since this dimension is the one achieving the most variance (table 1), little information is given in literature for explaining this uncertain behavior. Moreover, although clusters of questions belonging to the same style are represented on each factor in all studies considered here, both the absolute values of coefficients and the number of questions highly loaded on each factor lead to conclude for the presence of dependencies in ILS dimensions.

		A/R	S/I	V/V	S/G
			Factor 1		
$> \lvert .2 \rvert$	+				28
	-	29, 1	6	11, 23, 7, 19, 3, 27, 31, 43	
$> \lvert .1 \rvert$	+	17	26		4
	-		2, 38, 18	35, 39	32, 16, 12
			Factor 2		
$> \lvert .3 \rvert$	+		38		
$> \lvert .2 \rvert$	+		22, 10, 18, 6, 2, 30, 14		36, 44
$> \lvert .1 \rvert$	+		34, 42, 26		20, 4, 8, 28
	-	25, 33, 9, 41, 37		11, 31, 15, 7	
			Factor 3		
$> \lvert .4 \rvert$	-	37			
$> \lvert .2 \rvert$	-	21, 5, 13, 1, 9, 41	6		
$> \lvert .1 \rvert$	+		30, 22, 2	3, 23	
	-	25, 29,	38, 10, 18,	39	

Table 5 – Factor loadings of first 3 PCA factors (singular values greater than 20) for the ILS *M* matrix

For all these reasons it seems then reasonable to hypothesize that the basic assumption of ILS, that is that every pairwise coupled styles belong to the same latent dimension in opposite ways, has to be investigated in depth using appropriate and coherent statistical procedures.

From a statistical viewpoint, in fact, great differences arise when the multivariate dependencies between clusters of ILS questions are searched according to a data driven approach, with respect to when only the scores are considered.

Moreover, according to Theory of Measurement [15, 16] the quantities *i(DIM, q)* are measured on a scale quite near to the ordinal one, and the frequencies mapping is not surjective since $f(q_i^{DIM+}) = \sum_{q \in DIM+} q_i \in \mathbb{Z}^+$ while $i(DIM, q) \in \mathbb{Z}$ that is, while frequencies are always positive, *i(DIM, q)* can be also negative, and for this reason cannot be considered "variable" in strict sense.

Eventually, a comparison of these outcomes with the results presented in section 3 evidence the great difference that different data representation could bring to the analysis outcomes and the sensitivity of statistical methods for data representation: this points also out the coherence and consistency of data with statistical assumption of the methods employed.

6. Conclusions

In this paper, a data driven analysis of ILS relationships is presented. The outcome leads to some unexpected results that have been analyzed and compared with other analyses [6,13,19].

It seems reasonable to conclude that learning style identified by ILS present consistent dependencies between some styles, that the analysis of pairwise coupled dimensions is not able to detect. This leads to suggest that ILS questionnaire assesses dimensions that are not unidimensional, but rather bidimensional and also to conclude for a scarce validity and reliability of ILS questionnaire.

While, in order to accept the hypothesis, deeper and appropriate tests are needed, the effectiveness of data driven approaches, as well as the importance of a knowledge representation coherent and consistent with mathematical and statistical assumptions required by methods employed is pointed out. In particular, it is shown the importance of the whole data analysis process for effective, accurate and precise models both for applications and for research.

Moreover, an in depth investigation and a comparison of these results with data driven approaches based on usage data analysis for learning style detection, as in [7], seems to be promising for characteristics detection.

Thanks to the wide application of FSLSM in E-Learning Systems, especially for learners' profiling and contents recommendation, relevant relapses in E-Learning Systems can be foreseen.

7. References

[1] V. Cherkassky, and P. Mulier, *Learning from data*, Wiley, New York, 1998.
[2] L. J. Cronbach, "Coefficient alpha and the internal structure of tests", in *Psychometrika*, 16:297-333, 1951.
[3] S. Draper, "Observing, Measuring and Evaluating a Courseware: a Conceptual Introduction", in *Implementing Learning Technologies*, pp. 58-65, Learning Technology Dissemination Initiative, 1996, online at http://www.icbl.hw.ac.uk/ltdi/implementing-it/measure.pdf, retrieved august 3, 2006.
[4] R. M. Felder, and L. K. Silverman, "Learning and Teaching Styles in Engineering Education", *Engineering Education*, 78(7): 674-681, 1988; preceded by a preface in 2002: http://www.ncsu.edu/felderpublic/Papers/LS-1988.pdf retrieved 23 July, 2005.
[5] R. M. Felder, and B. A. Soloman, *Index of Learning Styles Questionnaires*, Online version (1997).Retrieved 6 May, 2006, from http://www.engr.ncsu.edu/learningstyles/ilsweb.html
[6] R. M. Felder, and J. Spurlin, "Applications, Reliability and Validity of the Index of Learning Styles", *Int. J. on Engineering Education*, 21(1): 103-112, 2005.
[7] S. Graf, and Kinshuk, "An Approach for detecting Learning Styles in Learning Management Systems", *Proc. of 6th IEEE Int. Conf . on Advanced Learning Technologies* (ICALT), IEEE Computer Society Press, Los Alamitos, CA, USA, pp. 161-163, 2006.
[8] S. Graf, S. R. Viola, Kinshuk, and T. Leo, "Representative Characteristics of Felder-Silverman Learning Styles: an empirical model", submitted to *IADIS Int. Conf. on Cognition and Exploratory Learning in the Digital Age (CELDA 2006)* , 2006.
[9] M. Greenacre, *Theory and Applications of Correspondence Analysis*, Academic Press, London, 1984.
[10] T. Hill, and P Lewicki, *STATISTICS. Methods and Applications*, StatSoft, Tulsa, OK, USA, 2006 (also available online at http://www.statsoft.com/textbook/stathome.html , retrieved august 1, 2006).
[11] T. I. Jolliffe, *Principal Component Analysis*, Springer, Berlin, 1986.
[12] L. Lebart, M. Morineau, and K. M. Warwick, *Multivariate Descriptive Statistical Analysis*, Wiley, New York, 1984
[13] T. A. Litzinger, S. H. Lee, and J. C. Wise, "A Study of the Reliability and Validity of the Felder-Solomon Index of Learning Styles", *Proc. of the 2005 American Society for Engineering Annual Conference and Exposition*, 2005, online at http://www.ncsu.edu/felder-public/ILSdir/Litzinger_Validation_Study.pdf, retrieved august 2, 2006.
[14] S. Siegel, and N. J. Castellan, *Nonparametric Statistics for the Behavioral Sciences* McGraw Hill, New York, 1988.
[15] S. S. Stevens, "On the theory of scales of measurement", *Science,* 103:677-680, 1946.
[16] L. Wilkinson, *The Grammar of Graphics*, Springer, Berlin, 1999 (1st edition)
[17] M. S. Zywno, "A Contribution to Validation of Score Meaning for Felder-Soloman's Index of Learning Styles", *Proc. of the 2003 American Society for Engineering Annual Conference and Exposition*, 2003, online at http://www.ncsu.edu/felder-public/ILSdir/Zywno_Validation_Study.pdf, retrieved august 2, 2006.