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Applications, Reliability and Validity of the Index of Learning Styles*

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The Index of Learning Styles© (ILS) is an instrument designed to assess preferences on the four dimensions of the Felder-Silverman learning style model. The Web-based version of the ILS is taken hundreds of thousands of times per year and has been used in a number of published studies, some of which include data reflecting on the reliability and validity of the instrument. This paper seeks to provide the first comprehensive examination of the ILS, including answers to several questions: (1) What are the dimensions and underlying assumptions of the model upon which the ILS is based? (2) How should the ILS be used and what misuses should be avoided? (3) What research studies have been conducted using the ILS and what conclusions regarding its reliability and validity may be inferred from the data?

LEARNING STYLES AND THE FELDER-SILVERMAN MODEL

STUDENTS have different strengths and preferences in the ways they take in and process information—which is to say, they have different *learning styles*. Some prefer to work with concrete information (facts, experimental data) while others are more comfortable with abstractions (theories, symbolic information, mathematical models). Some are partial to visual presentation of information—pictures, diagrams, flowcharts, schematics, etc., and others get more from verbal explanations. Some like to learn by trying things out and seeing and analyzing what happens, and others would rather reflect on things they plan to do and understand as much as they can about them before actually attempting them. When the learning styles of most students in a class and the teaching style of the professor are seriously mismatched, the students are likely to become uncomfortable, bored and inattentive in class, do poorly on tests, get discouraged about the courses, the curriculum and themselves, and in some cases change to other curricula or drop out of school [1, 2].

In 1988, Richard Felder and Linda Silverman formulated a learning style model designed to capture the most important learning style differences among engineering students and provide a good basis for engineering instructors to formulate a teaching approach that addresses the learning needs of all students [1, 3]. The model classifies students as having preferences for one category or the other in each of the following four dimensions:

- *sensing* (concrete thinker, practical, oriented toward facts and procedures) or *intuitive* (abstract thinker, innovative, oriented toward theories and underlying meanings);
- *visual* (prefer visual representations of presented material, such as pictures, diagrams and flow charts) or *verbal* (prefer written and spoken explanations);
- *active* (learn by trying things out, enjoy working in groups) or *reflective* (learn by thinking things through, prefer working alone or with a single familiar partner);
- *sequential* (linear thinking process, learn in small incremental steps) or *global* (holistic thinking process, learn in large leaps).

Detailed descriptions of the characteristics of these learning preferences are given in References 1 and 3.

Each of the stated dimensions has parallels in other learning style models, although the combination is unique to this one. The active/reflective dimension is analogous to the same dimension on the learning style model of Kolb [4, 5], and the active learner and reflective learner are respectively related to the extravert and introvert of the Myers-Briggs Type Indicator [6]. The sensing/intuitive dimension is taken directly from the MBTI and may have a counterpart in the concrete/abstract dimension of the Kolb model. The active/reflective and visual/verbal dimensions have some analogs in the visual–auditory–kinesthetic formulation of modality theory [7] and neurolinguistic programming [8], and the visual/verbal distinction is also rooted in cognitive studies of information processing [9–11].

The sequential/global dimension has numerous analogs. Students who have the characteristics of sequential learners have been referred to as left-brain dominant [5, 12, 13], atomistic [14], analytic [15], serialist [16] and auditory–sequential [17], and students with global learning traits have been

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termed right-brain dominant [5, 12, 13], holistic [14, 16], hierarchical [15] and visual–spatial [17]. Das [18] cites cognitive processing studies that have established the existence of two information coding schemes: successive coding, in which information is organized temporally (sequentially), and simultaneous coding, in which separate units of information are synthesized into a quasi-spatial, relational organization (globally). Schmeck [19] believes that the sequential–global dichotomy is 'the major dimension of cognitive style affecting learning'.

Regarding the orthogonality of the four dimensions, one would anticipate a moderate correlation between the sensing/intuitive and sequential/global scales. Sequential learners, who acquire understanding in logical connected steps, could be either sensors or intuitors, but global learners, whose thinking processes tend to be nonlinear and who acquire understanding holistically, would seem much more likely to be intuitive than sensing. Supporting this conjecture in the context of the Myers-Briggs Type Indicator, Lawrence [6] suggests that sensors and intuitive judgers should be sequential thinkers and intuitive perceivers should be more global. The possibility of another association between dimensions is suggested by Silverman [17], who presents evidence from brain hemisphere research and clinical observations that global ('visual–spatial') learners are more likely to be visual processors and sequential ('auditory–sequential') learners are more likely to be verbal processors. The linkage may not apply to the categories of the Felder-Silverman model, however, since when Silverman speaks of 'visual' learners she is thinking more of internal processing (such as visualization) than sensory input. There is no theoretical basis for expecting the active/reflective scale to correlate with any of the other three scales.

THE INDEX OF LEARNING STYLES

The Index of Learning Styles (ILS) is a 44-question instrument designed to assess preferences on the four dimensions of the Felder-Silverman model. An initial version was created in 1991 by Richard Felder and Barbara Soloman of North Carolina State University. In 1994 several hundred sets of responses to Version 1 were collected and subjected to factor analysis, and items that did not load significantly on single factors were discarded and replaced by new items to create the current version. A pencil-and-paper version of the instrument was put on the World Wide Web in 1996 and an on-line version was added in 1997 [20].

When someone submits a completed ILS questionnaire on-line, a profile is immediately returned with scores on all four dimensions, brief explanations of their meaning, and links to references that provide more detail about how the scores should and should not be interpreted. The ILS is available at no cost to individuals who wish to assess their own preferences or to instructors or students who wish to use it for classroom instruction or research, and it may be licensed by non-educational organizations.

Each learning style dimension has associated with it 11 forced-choice items, with each option (*a* or *b*) corresponding to one or the other category of the dimension (e.g., active or reflective). For statistical analyses, it is convenient to use a scoring method that counts '*a*' responses, so that a score on a dimension would be an integer ranging from 0 to 11. Using the active–reflective dimension as an example, 0 or 1 '*a*' responses would represent a strong preference for reflective learning, 2 or 3 a moderate preference for reflective, 4 or 5 a mild preference for reflective, 6 or 7 a mild preference for active learning, 8 or 9 a moderate preference for active, and 10 or 11 a strong preference for active. This method was used in all of the statistical analyses to be reported. (The method actually used to score the pencil-and-paper and on-line versions of the instrument subtracts the '*b*' responses from the '*a*' responses to obtain a score that is an odd number between -11 to $+11$.)

USES AND MISUSES OF LEARNING STYLES AND THE ILS

According to Keefe [21], learning styles are 'characteristic cognitive, affective and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment'. While Keefe's definition can serve to characterize the learning style preferences that the Felder-Silverman (FS) model articulates and the Index of Learning Styles (ILS) assesses, several qualifying statements are needed to clarify the intended uses of the instrument and guard against possible misuses.

- *Learning style dimensions—such as the four dimensions of the FS model—are continua, not either/or categories.* A student's preference for one or the other pole of a given dimension (visual or verbal, active or reflective . . .) may be mild, moderate, or strong.
- *Learning style profiles suggest behavioral tendencies rather than being infallible predictors of behavior.* While the characteristics of, say, sensors and intuitors are commonly presented as distinct and contradictory traits and behaviors, neither pure sensors nor pure intuitors can be found in nature: all sensors behave like intuitors in some situations and all intuitors sometimes behave like sensors. The way to think about it is that when students experience a large and diverse assortment of learning situations, those classified as sensors will behave in a manner characteristic of sensors more often than they will behave like intuitors—much more often if their preference for sensing is strong, slightly more often if their preference is mild.

- *Learning style preferences are not reliable indicators of learning strengths and weaknesses.* The fact that a student prefers sensing provides no sure measure of his or her skill at tasks associated with either sensing or intuition. The claim is that students classified as sensors are more likely to have strengths associated with sensing and to lack of strength associated with intuition than are students classified as intuitors. The stronger the preference, the greater the likelihood.
- *Learning style preferences can be affected by a student's educational experiences.* If, for example, a student with a strong preference for sensing takes a well-taught course that provides guided practice in intuitive skills, the student's comfort level with abstract conceptualization might increase and the strength of his/her preference for sensing might decrease accordingly.
- *The point of identifying learning styles is not to label individual students and modify instruction to fit their labels.* While studies have shown that greater learning may occur when teaching styles match learning styles than when they are mismatched [1, 19, 22, 23], a strong case can be made against teaching exclusively to accommodate learning style preferences. To function effectively as professionals, students will need skills associated with both categories of each learning style dimension; if they are never given practice in their less preferred categories, they will not develop the skills that correspond to those categories [1, 2]. The optimal teaching style is a balanced one in which all students are sometimes taught in a manner that matches their learning style preferences, so they are not too uncomfortable to learn effectively, and sometimes in the opposite manner, so they are forced to stretch and grow in directions they might be inclined to avoid if given the option.

This argument suggests what the authors consider to be the most important application of learning styles, which is designing effective instruction. Having a framework for identifying the different types of learners can help an instructor formulate a teaching approach that addresses the needs of all students. Moreover, determining the learning style profile of a class using an instrument such as the Index of Learning Styles (without being overly concerned about which student has which preferences) provides additional support for effective instructional design. For example, knowing that a large majority of students in a class are sensing and visual learners can—and should—motivate an instructor to find concrete and visual ways to present material that might normally be presented entirely abstractly and verbally.

What about identifying individual students' learning styles and sharing the results with them? Doing so can provide them with valuable clues about their possible strengths and weaknesses and indications of things they might work on to improve their academic performance. Precautions should be taken if this is done, however. The instructor should emphasize that any learning style instrument is fallible when applied to individuals, and if the students' perceptions of how they learn best differ from what the instrument says, they should not discount their own judgment. They should also be assured that their preferences are not reliable indicators of what they are and are not capable of doing, and that people with every possible learning style can succeed in any profession or endeavor. If a student comes out as a sensing learner on the ILS, it does not mean that he should avoid science or math at all costs, nor does it excuse the low grade he made on his last physics test. Instructors or advisors who use learning styles as a basis for recommending curriculum or career choices are misusing the concept and could be doing serious disservices to their students and advisees. The claims for validity of the Index of Learning Styles that follow presume that the instrument is being used in a manner consistent with these observations.

STUDIES UTILIZING THE ILS

Response data for the Index of Learning Styles have been collected in a number of studies. Some investigators simply measured and reported response profiles and drew inferences from them regarding appropriate teaching methods for their classes, and others used the profiles to examine various aspects of student performance and attitudes. This section summarizes the results of these studies, and the next section analyzes the results that bear on instrument reliability and validity.

Table 1 summarizes learning style profiles reported in different studies. Unless otherwise indicated, the samples are undergraduate students. Thus, for example, of the 129 undergraduate engineering students who completed the ILS in a study conducted at Iowa State University, 63% were classified as active learners (and by implication 37% were classified as reflective learners), 67% were sensing learners (so that 33% were intuitive learners) and so on.

Several studies also tabulate respondent profiles according to the strengths of the reported preferences, as shown in Table 2. For example, in the active–reflective dimension, 27% of the 85 students in the 2000 cohort at Ryerson University submitted between 8 and 11 '*a*' responses [indicating a moderate (8–9) or strong (10–11) preference for active learning], 58% submitted 4–7 '*a*' responses [mild active (6–7) or mild reflective (4–5)] and 15% submitted 0–3 '*a*' responses [moderate (2–3) or strong (0–1) reflective].

Table 2 shows large percentages of students with mild preferences. An implication is that when carrying out research on learning style differences in behavior and attitudes, the researcher would do well to examine only students with moderate or strong preferences. The students

Table 1. Reported learning style preferences

SAMPLED POPULATION	A	S	Vs	Sq	N	Reference
Iowa State, Materials Engr.	**63%**	**67%**	**85%**	**58%**	**129**	**Constant [24]**
Michigan Tech, Env. Engr.	**56%**	**63%**	**74%**	**53%**	**83**	**Paterson [25]**
Oxford Brookes Univ. , Business	64%	70%	68%	64%	63	**De Vita [26]**
British students	**85%**	**86%**	**52%**	**76%**	**21**	
International students	52%	62%	76%	52%	42	
Ryerson Univ., Elec. Engr.						
Students (2000)	**53%**	**66%**	**86%**	**72%**	**87**	**Zywno & Waalen [27]**
Students (2001)	**60%**	**66%**	**89%**	**59%**	**119**	**Zywno [28]**
Students (2002)	**63%**	**63%**	**89%**	**58%**	**132**	**Zywno [29]**
Faculty	**38%**	**42%**	**94%**	**35%**	**48**	
‘Tulane, Engr.						
Second-Year Students	**62%**	**60%**	**88%**	**48%**	**245**	**Livesay *et al.* [30]**
First-Year Students	**56%**	**46%**	**83%**	**56%**	**192**	**Dee *et al.* [31]**
Universities in Belo Horizonte (Brazil)[b]						
Sciences	65%	81%	79%	67%	214	Lopes [32]
Humanities	52%	62%	39%	62%	235	
Univ. of Limerick, Mfg. Engr.	**70%**	**78%**	**91%**	**58%**	**167**	**Seery *et al.* [33]**
Univ. of Michigan, Chem. Engr.	**67%**	**57%**	**69%**	**71%**	**143**	**Montgomery [34]**
Univ. of Puerto Rico-Mayaguez						
Biology (Semester 1)	65%	77%	74%	83%	39	Buxeda & Moore [35]
Biology (Semester 2)	51%	69%	66%	85%	37	Buxeda & Moore [35]
Biology (Semester 3)	56%	78%	77%	74%	32	Buxeda & Moore [35]
Elect. & Comp. Engr.	47%	61%	82%	67%	?	Buxeda *et al.* [36]
Univ. of São Paulo, Engr.[b]	60%	74%	79%	50%	351	Kuri & Truzzi [37]
Civil Engr.	69%	86%	76%	54%	110	
Elec. Engr.	57%	68%	80%	51%	91	
Mech. Engr.	53%	67%	84%	45%	94	
Indust. Engr.	66%	70%	73%	50%	56	
Univ. of Technology Kingston, Jamaica	**55%**	**60%**	**70%**	**55%**	**?**	**Smith *et al.* [38]**
Univ. of Western Ontario, Engr.[c]	69%	59%	80%	67%	858	Rosati [39]
First year engr	66%	59%	78%	69%	499	Rosati [40]
Fourth year engr.	72%	58%	81%	63%	359	Rosati [40]
Engr. faculty	51%	40%	94%	53%	53	Rosati [40]

[a] Rows in boldface denote studies using the current version of the ILS with native English speakers
[b] Portuguese translation of the ILS used
[c] Data collected with Version 1 of the ILS. (All other studies used Version 2.)

Table 2. Strengths of Preferences

	Act-Ref			Sens-Int			Vis-Vrb			Seq-Glo		
	Mod-Str Act	Mild	Mod-Str Ref	Mod-Str Sens	Mild	Mod-Str Int	Mod-Str Vis	Mild	Mod-Str Vrb	Mod-Str Seq	Mild	Mod-Str Glo
A1	27%	58%	15%	38%	52%	11%	69%	28%	3%	34%	52%	15%
A2	32%	50%	18%	38%	50%	12%	64%	32%	5%	21%	63%	16%
A3	30%	55%	15%	36%	49%	15%	62%	35%	3%	24%	62%	14%
B1	–	60%	–	–	52%	–	–	36%	–	–	58%	–
B2	–	55%	–	–	47%	–	–	36%	–	–	62%	–
B3	–	61%	–	–	52%	–	–	45%	–	–	64%	–
C	24%	61%	15%	43%	46%	11%	61%	34%	5%	31%	58%	11%
D	31%	54%	15%	48%	38%	14%	38%	45%	17%	20%	69%	11%
E	25%	69%	6%	49%	46%	5%	46%	48%	6%	29%	64%	7%
F	19%	65%	16%	33%	51%	16%	10%	61%	29%	27%	57%	15%

A1—Ryerson University, Engineering Students, 2000 cohort: $N = 87$ [29]
A2—Ryerson University, Engineering Students, 2001 cohort: $N = 119$ [29]
A3—Ryerson University, Engineering Students, 2002 cohort: $N = 132$ [29]
B1—San Jose State University, Materials Engineering Students, $N = 261$ [41]
B2—San Jose State University, Mechanical Engineering Students, $N = 196$ [41]
B3—San Jose State University, Freshman Engineering Students, $N = 693$ [41]
C—San Jose State University, Engineering Students, $N = 183$ [42]
D—Arizona State University, Graduate Students in Social Work [42]
E—Brazilian science students, $N = 214$ [32]
F—Brazilian humanities students, $N = 235$ [32]

with mild preferences would be expected to shift between categories readily rather than consistently exhibiting behavior associated with a single category, thereby masking style differences that might appear in students with stronger preferences.

RELIABILITY AND VALIDITY OF ILS SCORES

Unless otherwise indicated, the analyses to be described will include only results obtained administering the current English-language version of the instrument to native English speakers (the studies shown in boldface in Table 1). Issues regarding the accuracy of translations into other languages or comprehension of test items by non-native speakers thus need not be considered.

Test-retest reliability

Test-retest reliability measurements have been carried out by Livesay *et al.* [30], Seery *et al.* [33] and Zywno [43]. The results are reported in Table 3.

When determining test-retest reliability, the interval between test administrations should be large enough so that subjects cannot remember their responses from one administration to the next, but not so large that the quantity being assessed might change to a significant extent in the natural course of events. The 4-week interval used by Seery *et al.* [33] is ideal for this purpose. The high correlations reported in that study and the statistical significance of the other reported correlations—even after an interval of eight months and with a sample size as small as 24-support a conclusion that the test-retest reliability of the ILS scores is satisfactory.

Internal consistency reliability and inter-scale orthogonality

Internal consistency reliability refers to the homogeneity of items intended to measure the same quantity (e.g., the active/reflective preference) that is, the extent to which responses to the items are correlated. Cronbach's coefficient alpha, an average of all possible split pair correlations, is a common metric for this form of reliability. Different criteria of acceptability for alpha are appropriate for tests of two different types [44]:

- the quantity being measured is univariate, as in an achievement test of knowledge of a subject area or mastery of a particular skill;
- the quantity being measured reflects a preference or an attitude.

The preferences assessed by the Index of Learning Styles fall into the second category.

Consider, for example, a test that purports to measure a mathematical skill, such as proficiency at matrix algebra. The ability to perform matrix operations—transposition, addition, multiplication, inversion, etc.—is not situationally dependent: one either has those skills or not. Subjects who have received extensive training in matrix algebra should answer most test items correctly and subjects who have received little or no training should answer most of them incorrectly. A high level of internal consistency among the items and a correspondingly high Cronbach alpha would therefore be expected in a valid instrument.

On the other hand, attitudes in general and learning style preferences in particular are situationally dependent and do not necessarily become more pronounced with training or maturation. In fact, the opposite is often true of learning styles: if education does its job well, students should acquire the judgment to use their less preferred style modalities when appropriate and the skill to use them effectively. If they begin with a strong preference for one category or the other of a learning style dimension, this process will move them toward a position of greater balance, which in turn would lead them to respond differently to different items on the same scale of the ILS. If responses to items related to the same learning style dimension exhibited a very high internal consistency—say, a Cronbach alpha of 0.8 or higher—the implication would be that the items are not assessing independent aspects of the construct in question but are simply reworded variants of the same question. In light of these considerations, Tuckman [44] suggests that an alpha of 0.75 or greater is acceptable for instruments that measure achievement and 0.5 or greater is acceptable for attitude assessments. We will accordingly take $\alpha = 0.5$ as the criterion of acceptability for the ILS.

Table 4 shows values of α determined in four different studies. All of the alpha values exceed the criterion value of 0.5 except the one for the sequential–global dimension determined by Van Zwanenberg *et al.* [45], whose values for all dimensions are consistently lower than those determined in the other studies.

Pearson correlation coefficients for preferences on different scales were calculated in four studies,

Table 3. Test-Retest Correlation Coefficients

Δt	A-R	S-N	Vs-Vb	Sq-G	N	Reference
4 wk.	0.804**	0.787**	0.870**	0.725**	46	Seery *et al.* [33]
7 mo.	0.73*	0.78*	0.68*	0.60*	24	Livesay *et al.* [30]
8 mo.	0.683**	0.678**	0.511**	0.505**	124	Zywno [43]

*$p < .05$ **$p < .01$.

Table 4. Cronbach Alpha Coefficients

A-R	S-N	Vs-Vb	Sq-G	N	Source
0.56	0.72	0.60	0.54	242	Livesay *et al.* [30]
0.62	0.76	0.69	0.55	584	Spurlin [46]
0.51	0.65	0.56	0.41	284	Van Zwanenberg *et al.* [45]
0.60	0.70	0.63	0.53	557	Zywno [43]

with the results shown in Table 5. Three of the scales are reasonably orthogonal, but the sensing–intuitive and sequential–global preferences are correlated. Factor analyses of ILS responses were also carried out as part of three of the four studies cited in Table 5, all using the rotated principal component method [30, 43, 45]. All three studies concluded that the active–reflective, sensing–intuitive and visual–verbal scales may be considered independent but the sequential–global and sensing–intuitive scales show a moderate degree of association, confirming the conclusion drawn from the interscale correlations.

The most thorough of the factor analyses is that carried out by Zywno [43] for a sample of 551 respondents. Her initial analysis yielded 14 factors that satisfied the Kaiser criterion (eigenvalues less than 1.0), accounting for 54.1% of the total variance. Zywno then used the 'Scree plot' test, wherein eigenvalues are plotted vs. component numbers and components are ignored beyond the point where the rate of decrease in the eigenvalues undergoes a distinct discontinuity (from rapidly decreasing to slowly decreasing). The number of factors extracted in this manner was reduced to five. An oblique rotation was then applied, leading to the distribution of high loading items shown in Table 6. The first three scales are again seen to be relatively independent, and the sequential/global items load predominantly on Factor 5 but overlap somewhat with the sensing/intuitive items. A component correlation matrix shown by Zywno lends further support to this conclusion, with all off-diagonal elements being less than 0.1 except for the Factor 1 (sensing/intuitive) to Factor 5 (sequential/global) correlation coefficient, which is 0.220.

As noted in the introductory description of the Felder-Silverman model, the correlation between the sensing–intuitive and sequential–global scales is not unexpected, and in fact its occurrence supports the construct validity of the ILS. While perhaps problematic from a psychometric point of view, this inter-scale correlation does not pose a concern from the standpoint of the principal intended application of the ILS, which is to help instructors formulate a balanced teaching style. The sensing–intuitive and sequential–global dimensions represent different aspects of learning, and the instructional methods needed to address preferences on one scale are distinct from those needed to address preferences on the other [1, 3]. If it turns out that some of the methods that meet the needs of intuitive learners also benefit global learners, the instructor's task becomes that much easier.

Construct validity

Construct validity signifies the extent to which an instrument actually measures the theoretical construct or trait that it purports to measure. The instrument scores are said to have convergent construct validity if they correlate with quantities with which they should correlate and divergent or discriminant construct validity if they fail to correlate with quantities with which there is no reason to expect correlation. The results from several cited studies provide evidence addressing one or both of these forms of validity.

Learning style preferences are expected to influence students' tendencies to gravitate toward certain fields of study. Students who choose to major in a relatively abstract field such as mathematics or physics might be expected to be predominantly intuitors, for instance, while students who go into a more practical field such as civil engineering or nursing would be more likely to be sensors. Similarly, one would expect much higher percentages of artists and architects than of writers

Table 5. Interscale Correlations

	A-R	Sq-G	S-N
Sq-G	-0.04^{a}		
	0.07^{b}		
	0.07^{c}		
	0.08^{d}		
S-N	0.03^{a}	$0.48^{a,*}$	
	-0.06^{b}	$0.41^{b,**}$	
	$0.18^{c,**}$	$0.32^{c,**}$	
	0.01^{d}	$0.55^{d,**}$	
Vs-Vb	0.03^{a}	-0.07^{a}	-0.06^{a}
	0.15^{b}	0.07^{b}	-0.04^{b}
	0.08^{c}	-0.09^{c}	0.11^{c}
	$0.18^{d,**}$	0.03^{d}	0.03^{d}

[a] Livesay *et al.* [30], $N = 242$
[b] van Zwanenberg *et al.* [45], $N = 284$
[c] Zywno [43], $N = 557$
[d] Spurlin [46], $N = 584$
$*p < 0.01$
$**p < 0.001$

Table 6. Distribution of high loading items in factor analysis

Factor →	1	2	3	4	5
Act/Ref	2		7		
Sen/Int	9			2	2
Vis/Vrb		8			
Seq/Glo				2	5

and linguists to be visual learners. Generalizing these statements, one would expect undergraduates attracted to a specific field (say, engineering) to display relatively similar profiles from one year to another at similar institutions, with those profiles on average differing noticeably from profiles of students in a much different field (such as one of the humanities).

Ten eligible engineering student populations are shown in Table 1 (with 'eligible' meaning native English speakers using the current English-language version of the test): three at Ryerson, two at Tulane, and one each at Kingston, Iowa State, Limerick, Michigan and Michigan Tech. The means and standard deviations of the preferences were 61% active (SD = 6%), 63% sensing (SD = 8%), 82% visual (SD = 8%) and 59% sequential (SD = 7%). Undergraduate engineering students at a variety of different institutions are therefore consistently more active than reflective and more sensing than intuitive, much more visual than verbal, and more sequential than global (only the Tulane population of second-year students contained slightly more global than sequential students). The ranges of variation for students in a single discipline (electrical engineering) at one university (Ryerson) in three consecutive years were considerably narrower than the variations across disciplines and campuses, as would be expected. The similarities in the profiles of engineering students at different institutions and at the same institution in different years are even more apparent in Table 2. These results support a claim of convergent validity for the first three scales and to a lesser extent for the sequential–global scale.

The profiles shown in Table 1 for engineering faculty members show predictable differences from those of engineering students. The faculty at Ryerson University is significantly more reflective and intuitive ($p < 0.001$), both results being consistent with descriptions of student–faculty mismatches presented by Felder and Silverman [1] and Felder [3]. The Ryerson faculty is also significantly more global ($p < 0.0005$), a result that might not have been anticipated but is not inconsistent with the theory. All three of these results and the overwhelming preponderance of visual learners on the faculty match the engineering faculty profile obtained by Rosati [40] with the original version of the ILS and also shown in Table 1, further supporting the discriminant validity of the instrument.

The results shown in Table 1 for non-native English speakers cannot stand alone to affirm or negate the validity of the ILS, but several patterns in the results provide additional support for validity claims. The only predictable difference between different engineering disciplines is that civil engineering (arguably the most concrete of the disciplines—no pun intended) would be expected to attract proportionally more sensors than fields such as mechanical and electrical engineering, which place much more emphasis on abstract conceptualization and mathematical modeling in topics such as transport theory and thermodynamics (mechanical) and field theory and microelectronics (electrical). The results obtained by Kuri and Truzzi [37] confirm this hypothesis. Similarly, one would expect students in the humanities to be proportionally much more verbal than their counterparts in the sciences, an expectation dramatically confirmed by the results of Lopes [32] shown in Tables 1 and 2.

Rosati [47] has carried out the only published study in which the Myers-Briggs Type Indicator was administered to the same students as the Index of Learning Styles (Version 1). The only ILS scale that has an exact counterpart on the MBTI is sensing–intuitive. Rosati found that most students who were sensing on the ILS were also sensing on the MBTI, with the association being highly significant. There should also be a correlation between a preference for active learning on the ILS and extraversion on the MBTI, and indeed, Rosati found that active learners were significantly more extraverted and perceiving, both types that prefer experimentation and trial-and-error approaches to learning relative to introverts and judgers. Students who were clearly more sequential on the ILS were significantly more likely to be sensors than intuitors on the MBTI, supporting the conjecture of Lawrence [6] that sensors are likely to think sequentially while intuitors may favor either sequential learning (if they are also judgers on the MBTI) or global learning (if they are perceivers).

Zywno [27] taught a process control course using supplemental hypermedia instruction to a class of electrical engineering students and compared their performance with that of a control group taught conventionally. The outcome studied was grade in the course relative to a 'prior academic performance' measure (PAP) determined from grades in a prerequisite course and prior grade-point average. According to learning style theory, conventional instruction in engineering courses favors reflective learners (since students in traditional lecture courses are largely passive), intuitive learners (since the emphasis in most engineering courses is on theory and mathematical models), verbal learners (since most lectures and textbooks are predominantly verbal), and sequential learners (since most courses and textbooks follow fairly rigid sequences in their presentation of information and little is generally done to provide 'big picture' contextualization of course material) [1, 3]. Indeed, active, sensing and global learners were overrepresented among the students in Zywno's study whose PAP was below the median.

The hypermedia instruction in Zywno's course was designed to include instructional features that address the needs of the learning styles disadvantaged by conventional instruction. The hypothesis was that the improvement in the course relative to prior academic performance in the experimental group would be greater for the traditionally disadvantaged categories than for their opposites. That outcome was observed for all four learning style dimensions [27]. Comparable results were obtained in a later study by Zywno [28] except for those pertaining to the visual–verbal scale. Zywno attributed the latter result to the very small number of verbal learners in her sample. The relatively poor performance of the active, sensing and global learners in conventionally taught courses and the positive effect of the supplemental hypermedia instruction on those three types and the visual learners in the first year of the study are all consistent with predictions of the model upon which the ILS is based [1, 3].

SUMMARY AND CONCLUSIONS

Several analyses of responses to the Index of Learning Styles have been published. The principal results that bear on the reliability and validity of the instrument are as follows.

Test-retest correlation coefficients for all four scales of the instrument varied between 0.7 and 0.9 for an interval of four weeks between test administrations and between 0.5 and 0.8 for intervals of 7 months and 8 months. All coefficients were significant at the 0.05 level or better (Table 3).

Cronbach alpha coefficients were all greater than the criterion value of 0.5 for attitude surveys in three of four studies, and were greater than that value for all but the sequential-global dimension in the fourth study (Table 4). The values of the coefficients for each dimension in all but the latter study were remarkably consistent with one another.

Pearson correlation coefficients relating preferences on the different dimensions of the ILS were calculated in four studies (Table 5). The values were consistently 0.2 or less except for those relating the sensing–intuitive and the sequential–global dimensions, which ranged from 0.32 to 0.48. Factor analyses conducted as part of the same studies supported the conclusion that the active–reflective, sensing–intuitive and visual–verbal scales are orthogonal but the sequential–global and sensing–intuitive scales show some association. That association is consistent with the theory that underlies the Index of Learning Styles and does not compromise the validity of the instrument for its principal intended purpose of designing balanced instruction.

A consistent pattern of learning style preferences was found for engineering students at ten universities in four English-speaking countries, and the consistency was even greater when students in a single discipline at one university were compared in three successive years (Tables 1 and 2), demonstrating convergent construct validity. Learning style profiles of engineering faculty and of students in disciplines other than engineering show distinct, consistent and predictable differences from those of engineering students, demonstrating discriminant construct validity.

The conventional teaching approach used in engineering education emphasizes lectures over active engagement (favoring reflective and verbal learners over active and visual learners), focuses more on theoretical abstractions and mathematical models than on experimentation and engineering practice (favoring intuitive learners over sensing learners), and presents courses in a relatively self-contained manner without stressing connections to material from other courses or to the students' personal experience (favoring sequential learners over global learners) [1, 3]. Zywno [27] found that on average the performance in conventionally-taught courses of each of the favored types was superior to that of the less favored types, and she also found that the use of supplemental hypermedia instruction designed to address the needs of all types decreased the performance disparities.

Zywno [43] and Livesay *et al.* [30] concluded that their reliability and validity data justified a claim that the ILS is a suitable instrument for assessing learning styles, although both studies recommended continuing research on the instrument. We believe that our compilation of results supports that assertion. Van Zwanenberg *et al.* [45] concluded that the ILS is best used to allow individuals to compare the strengths of their relative learning preferences rather than offering comparisons with other individuals, basing this assertion in part on their lack of success in predicting academic performance from ILS scores. We have no quarrel with their conclusion; in fact, as we noted early in this paper, we do not believe that learning styles (as measured with the ILS or any other instrument) should ever be used to predict academic performance or draw inferences about what students are and are not capable of doing. Learning styles reflect preferences and tendencies; they are not infallible indicators of strengths or weaknesses in either the preferred or the less preferred categories of a dimension.

The Index of Learning Styles has two principal applications in our view. The first is to provide guidance to instructors on the diversity of learning styles within their classes and to help them design instruction that addresses the learning needs of all of their students. In particular, finding a large number of students with a specific preference whose needs are not being addressed should alert instructors to the need to make some changes in their teaching.

The second application is to give individual students insights into their possible learning strengths and weaknesses. Many students who consistently have difficulties with certain types of courses and instructors are inclined to place the blame entirely on poor teaching and accept no personal responsibility for their failures. Many others tend to take full responsibility, attributing the failures entirely to their own self-perceived inadequacies (as in, 'I'm just no good in math').

Students of both types who take the ILS and agree with the outcomes may find it helpful to reframe their difficulties in terms of conflicts between the instructor's teaching style and their learning style. Understanding what they need and are not getting in a class is the first step toward seeking what they need, in or out of class, and then working on skills associated with their less preferred styles. At the same time, some students (particularly global learners) may be conscious of their deficiencies but may not realize that they also have strengths, since traditional teaching does not address those strengths and seldom calls on students to exercise them. Learning what those strengths are can be empowering and even transformative [48].

In short, as long as the Index of Learning Styles is used to help instructors achieve balanced course instruction and to help students understand their learning strengths and areas for improvement (as opposed to being used to predict students' grades or dictate their course and curriculum choices), our analysis and the other published analyses suggest that the current version of the instrument may be considered reliable, valid and suitable.

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