Gender and Program Differences in Learning Styles of Students in Technology-Focused vs. Humanities Programs

Malgorzata S. Zywno
Ryerson University, Toronto, Canada
gosha@ee.ryerson.ca
Mary F. Stewart[1]

***Abstract* - Attrition rates in junior years of technology-focused programs, and particularly in engineering, have traditionally been higher than in humanities. Such trends are worrying and efforts are needed to better understand our students that would in turn allow the university to better plan and tailor their student success, retention and recruitment programs. The authors have recently started a longitudinal study that will follow a cohort of students through their undergraduate education at the authors' home university. As part of the study, a learning style questionnaire was administered to over 700 students in September 2006. While previous studies used that instrument with engineering students, the literature review found only one study that included humanities students. As well, the literature review found no data on gender differences, as students in engineering programs tend to be overwhelmingly male. This paper aims to contribute to the understanding of learning differences by providing analysis of learning style differences between genders and programs within the surveyed cohort.**

Index Terms – Learning Styles, Felder Model, Gender Differences.

BACKGROUND

Attrition rates are much higher in junior years of technology-focused programs than in humanities. At the authors' university, up to 30% of engineering students drop out at the end of their first year, a percentage typical when compared with other technology-focused programs. As well, in recent years technology-focused programs have been experiencing drops in enrollment, and difficulties in attracting qualified candidates, while admissions to other programs seem unaffected. Such trends are worrying and the educators need to improve efforts to better understand students' learning that would in turn allow the university to better plan and tailor their student success, retention and recruitment programs. The authors have recently embarked on a multi-year investigation into retention issues, learning differences and depth of learning aiming to improve student success and engagement in technology-focused programs at their home university. The study will follow a cohort of students through their undergraduate education from their entry into the first year in Fall 2006 to their graduation in Spring 2010. The authors currently hold national level government funding for the first three years of the project.

According to Richard Felder, a pre-eminent engineering educator, three categories of individual differences have implications for teaching and learning: learning styles, approaches to learning and intellectual development levels [1]. The authors want to develop a better understanding of student learning styles, maturity levels (emotional competency) as they progress through the four-year program, their response to instructional delivery methods, and their perceptions of the effectiveness of those strategies. The long-term goal of the project is to investigate why the defined outcomes of the learning process are significantly different in technology-focused programs when compared with humanities, and to formulate recommendations on how to improve retention and academic success of students in technology-focused programs. As the first step of the study, a survey was administered to over 700 first year students in September 2006. This paper deals with preliminary results obtained from the analysis of the survey, and is limited to learning styles only.

FELDER MODEL OF LEARNING STYLES

Learning style represents a manner in which learners consistently respond to and process information in a learning environment, and is defined by bipolar dimensions. While the concept of the learning style is not universally accepted, particularly among psychologists, the existing models of learning styles paint a consistent picture of learner differences and proved to be effective in tailoring instruction to support learner needs [1]. Several psychometric tools for different learning models have been used in educational research. In their research, the authors decided to adopt the model developed in 1988 by Felder, an engineering professor at North Carolina State University, with help of psychologist Linda Silverman that focuses on aspects of learning styles particularly significant in engineering education [1]-[2]. The model has four bipolar dimensions describing Perception (*Sensing-Intuitive*), Input (*Visual-Verbal*), Processing (*Active-Reflective*) and Understanding (*Sequential-Global*) of information, with scores in the range of 6-7 indicating a balanced learning style with mild preference either way,

[1] Mary F. Stewart, Ryerson University, Toronto, Canada, fstewart@ryerson.ca

scores in the range of 8-9, indicating a moderate preference, and scores in the range of 10-11 indicating strong preference for a particular mode of learning. In 1991, the psychometric assessment instrument, Felder-Soloman Index of Learning Styles, was developed [3]. The ILS is simple, non-ambiguous and in public domain. The web-based, 44-item, self-scoring version of the questionnaire gets approximately 100,000 hits per year and has been translated into several languages. Since its inception The ILS has gone through several iterations and many validation studies [4]-[6].

PLANNED INVESTIGATION OF LEARNING STYLES

While the ILS has been used in large studies to assess learning styles of engineering students [7]-[9], the literature review identified only one study of business students [10], one study of arts students [1], and none provided more than anecdotal speculation regarding possible gender and cultural differences in learning preferences, although both areas were identified by Felder as worthy of further investigations [1]. The authors thus saw an opportunity to make a contribution to the existing research on the ILS based on their access to student populations not previously included in any studies (i.e. arts students, women and students of diverse cultural backgrounds).

The planned longitudinal study will include an investigation of a *self-selection effect,* where students with certain learning style preferences seem to choose a particular field of study. For example, percentage of visual learners among engineering students is much higher than among the general population. Between 70% and a staggering 95% of engineering students are reported to be visual learners [1], [6], compared with 60% of high school students [11]. A majority of engineering students also prefer active learning, where they process information through physical activity, discussion, group work and meaningful projects relating to the "real world". Yet there is a mismatch between these preferences and traditional engineering instruction that is still overwhelmingly verbal, theoretical and lecture based [1]. This mismatch is believed to contribute to high attrition rates, poor academic performance, disillusionment that some students experience within a program, and negative perceptions about careers in engineering. The authors hypothesize that similar patterns are at work across all technology-focused programs.

The authors will also investigate whether a *filtering effect* is taking place, whereby diversity of the student body (as expressed by their learning styles) is reduced as they progress through the program. Their speculation regarding the filtering effect is based on the fact that literature review reveals differences in distributions of learning styles among students and faculty as well as between senior and junior level students [12]-[14]. Styles of senior and graduate students are more aligned with the faculty, while those of the lower level students' are more divergent. Some suggest that the learning styles of students undergo transitions [13], possibly as a result of the effect the particular program of study has on the students' learning strategies and habits. However, this theory is untested, since it has been asserted in the literature that learning style preferences do not change over time, regardless of the content matter or teaching methods [15]-[16], though Kolb [17] suggests that they become less pronounced as learners mature and develop cognitive flexibility.

Other studies show high correlation of the learning style assessments over time [4]-[5], supporting the hypothesis of learning styles being a constant trait. Thus, a longitudinal study is necessary to investigate if the shift in learning styles of individuals within a cohort actually takes place over time. In fact, a more compelling possibility for the changes in style distributions over time is that the style of teaching prevalent in the field adversely affects students with learning styles not supported by it. This would create the filtering effect of traditional learning environments, where learner differences are not acknowledged. Students whose learning styles are consistently not supported, thus have more problems remaining in their programs and drop out at higher rates [1]. Such "filtering" would reduce diversity of styles among the graduates, urgently needed by technology-focused professions.

Indeed, while engineering students on our campuses are now more ethnically diverse than ever, participation of women in engineering in North America, after a couple of decades of progress, has stalled around 20% and in fact has started to decline. Similarly, most creative, thinking-outside-the-box prospective students are turned off by traditional approaches to education and a silo mentality that permeates the technology-focused field. Currently, successful students seem to be those most resembling their professors in study habits. While this may make them good candidates to survive the rigors of a graduate program (and become academics themselves), since only a small fraction will continue on into graduate school, the skill sets they develop while in their undergraduate program may not be the best match for a successful technology-focused professional. Thus, the possible "filtering effect" of technology-focused programs warrants a serious investigation that will be provided in this study. If its existence is confirmed, it would provide useful insights into retention issues.

METHODS

The research protocol for the study was approved by the Ryerson Research Ethics Board. Student participation was voluntary, and all participating students were asked to sign an informed consent letter. The students were not exposed to any risks or reprisals for refusal to participate in the study. Volunteers for this study were drawn from three distinct student bodies on campus: engineering, business and general humanities programs. Students for the experimental cohort (technology-focused programs) were recruited from Engineering, and Information Technology (IT) Management programs. The study will track the students from entry into their first year in Fall 2006 to their graduation in Spring 2010. Four different questionnaires will be administered to the participants at different points of their program, and Focus Groups (FG) will be held with a smaller group of students on a yearly basis and taped for later assessment. The first round of surveys, completed in September 2006, had more than 700 volunteers. At the time of writing, the encoded data base included 503 entries from first semester students. That number included 298 engineering students and 84 Information Technology Management students, together comprising Technology-Focused (TF) cohort, and another 111 responses from the Humanities-Focused (HF) cohort. There were 357 ILS responses from male students and 136 ILS responses from female students. For this paper, the authors focused only on the analysis of the ILS part of the surveys collected.

Since the ILS questionnaires included in the current analysis were completed by the students who arrived on campus in the same month the survey was done, the learning style distributions represent *self-selection patterns* among the students who chose a particular field of study. The planned longitudinal study will examine whether the learning styles of individual students remain stable throughout their stay in the program, or whether the nature of the program itself has a modifying effect on the students' styles. It will also track retention rates for students with different learning styles to identify the possible filtering effect.

RESULTS AND DISCUSSION

The distribution of genders among the TF cohort was 85.3% male vs. 14.7% female, compared with an opposite trend among the HF cohort (27.9% male vs. 72.1% female). These two distributions are almost diametrically opposite, consistent with the well-known fact that technology-focused cohorts tend to be predominantly male, in itself a self-selection pattern. Table I shows bimodal distributions of learning styles among Engineering and Business students. There were no statistically significant differences between these two cohorts, thus confirming the validity of the approach where these two cohorts are considered comparable and are combined into one group referred to as Technology-Focused (TF) cohort.

TABLE I
DIFFERENCES IN BIMODAL DISTRIBUTIONS: ENG. VS. BUSINESS

Eng	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	173	125	190	108
%	58.1%	41.9%	63.8%	36.2%
Bus	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	48	36	54	30
%	57.1%	42.9%	64.3%	35.7%
χ^2 program differences	χ^2=0.029 p=0.866		χ^2=0.010 p=0.920	
Eng	**Visual**	**Verbal**	**Sequential**	**Global**
Number	270	28	196	100
%	90.6%	9.4%	66.2%	33.8%
Bus	**Visual**	**Verbal**	**Sequential**	**Global**
Number	74	10	55	29
%	88.1%	11.9%	65.5%	34.5%
χ^2 program differences	χ^2=0.621 p=0.431		χ^2=0.021 p=0.886	

** Significant at the 0.01 level (2-tailed).

Table II shows bimodal distributions of learning styles for the Technology-Focused (TF) cohort and the Humanities (HF) cohort. The participating TF students were overwhelmingly Visual learners (90%). They were also predominantly Active (58%), Sensing (64%) and Sequential (66%). This is consistent with previous research that shows the vast majority of students in technology-focused programs, are visual learners who achieve more subject-related understanding from pictures, diagrams or demonstrations [3],[5]-[10]. Their numbers are much higher than in the general population [11]. The 90% of TF students who were Visual learners is consistent with various studies quoted by Felder [6] where that percentage varied from 70% to 95%. The roughly 60%-40% split in favor of Active and Sensing modalities is also very consistent with the literature and supports the model construct that assumes that students in technology-focused programs show preference for active learning in a context of real-life applications, where they can engage with the subject in a meaningful way and to process information through physical activity, discussion or group work [6]-[9].

Finally, the 65%-35% split in favor of Sequential way of organizing knowledge is also consistent with the theoretical construct of the model showing that engineering students tend to prefer an orderly progression through topics and subjects without questioning underlying connections and with performing tasks with only a partial understanding of the subject. The construct also acknowledges the reality of traditional styles of instruction in engineering departments that reinforces these tendencies through an over-reliance on sequential lectures and rarely demands of students a more holistic approach to understanding [6]-[9].

TABLE II
DIFFERENCES IN BIMODAL DISTRIBUTIONS: TF VS. HF COHORT

TF	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	221	161	244	138
%	57.9%	42.1%	63.9%	36.1%
HF	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	63	48	28	83
%	56.8%	43.2%	25.2%	74.8%
χ^2 program differences	χ^2=0.055 p=0.815		χ^2=**71.856** **p=0.0001****	
TF	**Visual**	**Verbal**	**Sequential**	**Global**
Number	344	38	252	130
%	90.1%	9.9%	66.0%	34.0%
HF	**Visual**	**Verbal**	**Sequential**	**Global**
Number	79	32	76	35
%	71.2%	28.8%	68.5%	31.5%
χ^2 program differences	χ^2=**44.174** **p=0.0001****		χ^2=**58.992** **p=0.0001****	

** Significant at the 0.01 level (2-tailed).

As Table II shows, the participating HF students were also predominantly strongly or moderately Visual learners (71%), which is consistent with a documented shift over the last half a century in North America in information intake preferences among the general population from mostly text-based to visually-oriented, attributed to an explosion of visual media and computers [11]. However, the percentage of those students who were Verbal learners is much higher among the HF cohort than among the TF cohort (29% vs. 10%, respectively), and the difference is statistically significant, as shown in Table II. The differences between the two cohorts are even more striking, and statistically significant, for Processing and Understanding dimensions, where HF students were predominantly Intuitive (75%) and

Global (69%). Larger percentages of Verbal learners and the predominance of Intuitive and Global learners seem to be consistent with the nature of humanities programs that emphasize research and assimilation of large quantities of assigned readings, development of communication skills and a holistic approach to understanding of the domain. At the same time there is less room for practical experimentation so favored by Sensing learners.

In both cohorts in the current study an almost identical percentage of students are Active learners (57.1% in the TF cohort vs. 56.8% in the HF cohort) and the Active and Reflective preferences are the most balanced. Unlike the Input dimension, where the vast majority of all students are moderately or strongly Visual (the mean Visual score for the TF cohort was 8.40 out of 11 vs. 7.02 for the HF cohort), the mean scores for the Active mode of learning were much lower (6.05 for the TF cohort vs. 6.0 for the HF cohort), indicating a prevalence of a balanced learning style, with only a slight preference for Active learning. This is consistent with the very mechanism of how learning takes place, best elucidated by who introduced the concept of "experiential learning cycle" [17]. All learners need to experience and experiment, but also to reflect and analyze and thus tertiary level learners are expected to have developed a degree of cognitive flexibility that allows them to be Active learners at some times, and Reflective at other times.

It has been suggested that the differences in learning preferences between programs may be linked to a larger proportion of enrolled female students. Van Zwanenberg, in his study [10] of business vs. engineering students at the University of Newcastle, UK, found significant differences between these two populations in bimodal distributions on all dimensions, and speculated that it may be connected to the fact that there were many more females among business students than among engineering students, but did not provide detailed gender distributions between the two cohorts. Because studies using the ILS questionnaire tend to focus on engineering students, which traditionally are overwhelmingly male, the literature review did not find any other examples of gender differences analysis in learning preferences. The current study represents thus a unique opportunity to study these.

Table III shows bimodal distributions of learning styles for the male and female students. Both male and female populations show similar preference for Active mode of learning (57% of females vs. 58% of males). However, there are significant differences on other dimensions. More male learners are Sensing (58%) and Sequential (62%), while more female learners are Intuitive (52%), with Global and Sequential learners split equally among women. Both male and female students are overwhelmingly Visual learners, but the differentiation between the two genders is the strongest in this dimension, with a significantly larger proportion of Verbal learners among female students (25% vs. 10% among males).

A comparison of Table II and Table III shows that differences in bimodal distributions between male and female populations on Perception, Input and Understanding dimensions are very similar to those between the two cohorts (TF vs. HF). Since the HF cohort is overwhelmingly female and the TF cohort is overwhelmingly male, the question remains whether these differences are gender or program-based. Table IV and Table V show gender distributions within the programs.

TABLE III
DIFFERENCES IN BIMODAL DISTRIBUTIONS BY GENDER

Male	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	207	150	207	150
%	58%	42%	58%	42%
Female	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	77	59	65	71
%	56.6%	43.4%	47.8%	52.2%
χ^2 program differences	χ^2 =0.261 p=0.603		χ^2 =**14.854** **p=0.0001****	
Male	**Visual**	**Verbal**	**Sequential**	**Global**
Number	89.9%	10.1%	321	36
%	321	36	89.9%	10.1%
Female	**Visual**	**Verbal**	**Sequential**	**Global**
Number	102	34	68	67
%	75%	25%	50.4%	49.6%
χ^2 program differences	χ^2 =**42.361** **p=0.0001****		χ^2 =**16.813** **p=0.0001****	

** Significant at the 0.01 level (2-tailed).

TABLE IV
DIFFERENCES IN BIMODAL DISTRIBUTIONS BY GENDER, TF COHORT

TF Male	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	188	138	201	125
%	57.7%	42.3%	61.7%	38.3%
TF Female	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	33	23	43	13
%	58.9%	41.1%	76.8%	23.2%
χ^2 program differences	χ^2 =0.036 p=0.849		χ^2 =**5.422** **p=0.020***	
TF Male	**Visual**	**Verbal**	**Sequential**	**Global**
Number	297	29	213	113
%	91.1%	8.9%	65.3%	43.7%
TF Female	**Visual**	**Verbal**	**Sequential**	**Global**
Number	47	9	39	17
%	83.9%	16.1%	69.6%	30.4%
χ^2 program differences	χ^2 =3.558 p=0.059		χ^2 =0.458 p=0.498	

** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

Out of the eight comparisons made in Table IV and Table V (i.e. male vs. female distributions on four dimensions within the two cohorts), there were no statistically significant differences in six. The difference within the TF cohort on Sensing-Intuitive dimension is statistically significant (at 0.05 level) with more TF female students with a Sensing learning preference (78% vs. 62% among males). There is also a statistically significant difference within the HF cohort on Sequential-Global dimension, with significantly more HF male students with a Global learning preference (80.6% vs. 63.8% among females). However, the samples of female TF and male HF populations were small (n = 17 and 31, respectively), reducing the impact of such differences on the overall cohorts.

TABLE V

DIFFERENCES IN BIMODAL DISTRIBUTIONS BY GENDER, HF COHORT

HF Male	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	19	12	6	25
%	61.3%	38.7%	19.4%	80.6%
HF Female	**Active**	**Reflective**	**Sensing**	**Intuitive**
Number	44	36	22	58
%	55.0%	45.0%	27.5%	72.5%
χ^2 program differences	$\chi^2=1.334$ p=0.248		$\chi^2=3.400$ p=0.065	
HF Male	**Visual**	**Verbal**	**Sequential**	**Global**
Number	24	7	6	25
%	77.4%	22.6%	19.4%	80.6%
HF Female	**Visual**	**Verbal**	**Sequential**	**Global**
Number	55	25	29	51
%	68.8%	31.3%	36.3%	63.8%
χ^2 program differences	$\chi^2=3.439$ p=0.064		χ^2**=14.630 p=0.0001****	

** Significant at the 0.01 level (2-tailed).

SUMMARY

In summary, a strong evidence of self-selection mechanisms among the first year students was observed, suggesting that the programs tend to attract populations with different learning preferences, consistent with the program focus. Based on the analysis of the present sample, it would seem that gender has minimal effect on the learning style preferences, although further analysis of gender differences may still be warranted. The observed bimodal distributions for students in Engineering are very consistent with the theoretical model, proposed by Felder [1]. The distributions for Business students were not significantly different, thus justifying lumping these two programs together into a TF (Technology-Focused) cohort for the purpose of this study.

The bimodal distributions found in the HF (Humanities-Focused) cohort were almost opposite to those in the TF cohort, which seems to be consistent with the requirements of the program. However they are not consistent with the only study of humanities students found in the literature review [1]. A study of 235 humanities students in Belo Horizonte, Brazil, found them to be mostly Verbal learners (61%), while only 29% of the HF students in the current study were. The Brazilian study also showed that Sensing and Sequential learners accounted for 62% each, compared with only 25% and 32%, respectively, of the HF cohort in the current study.

One possible explanation may be that specifics of the single quoted study cannot be generalized. For example, we do not know whether the general population in Brazil is predominantly Visual, as it is in North America. Similarly, since there seems to be a self-selection component in choosing a program of study, perhaps there are cultural components to the Brazilian humanities curriculum that affect the distributions. It is also entirely possible that it is the HF students in the current study at Ryerson who are a distinct population, where learning preferences cannot be generalized. In either case, the ILS scales in context of the humanities programs should be further investigated.

In summary, the initial analysis supports the authors' original assertion that the Engineering and Business students can be considered together as the representative sample of students in Technology-Focused programs, and suggests that gender is not a significant factor in distributions of learning styles. However, significant differences in those distributions between the TF and HF cohort show promise of interesting insights to follow in the future stages of the research.

REFERENCES

[1] Felder, R.M. & Brent, R., "Understanding student differences", *J. Eng. Educ.*, Vol. 94, No. 1, 2005, pp. 57-72.

[2] Felder, R.M. & Silverman, L.K., "Learning and Teaching Styles in Engineering Education", *J. Eng. Educ.*, Vol. 78, No. 7, 1988, pp. 674-681.

[3] Felder, R.M. & Soloman, B.A., "Index of Learning Styles Questionnaire", Online at: http://www.engr.ncsu.edu/learningstyles/ilsweb.html [Accessed April 24, 2007].

[4] Livesay, G.A. & Dee, K.C., "Test-Retest Reliability of the Index of Learning Styles of First Year Engineering Students", *Proceedings of the 2005 ASEE Annual Conference and Exposition*, Portland, Oregon, June 12-15, 2005.

[5] Zywno, M.S., "A Contribution to Validation of Score Meaning for Felder-Soloman's Index of Learning Styles", in *Proc. ASEE Ann. Conf. and Exposition*, Session 2351, Nashville, TN, June 23-25, 2003.

[6] Felder, R.M., & Spurlin, J.E., "Applications, reliability, and validity of the Index of Learning Styles", *Int. J. Eng. Educ.*, Vol. 21, No. 1, 2005, pp. 103-112.

[7] Felder, R.M., Felder, G.N. & Dietz, E.J., "A longitudinal study of engineering student performance and retention, V: Comparisons with traditionally-taught students", *J. Eng. Educ.*, Vol. 87, No. 4, 1998, pp. 469-480.

[8] Zywno, M.S., "Improving Student Outcomes through Hypermedia Instruction - a Comparative Study", *British J. Eng. Educ*., UK, Vol. 3, No. 1, 2002, pp. 25-33.

[9] Zywno, M.S., "Learning Styles of Engineering Students and their Implications for Successful Teaching with Instructional Technology", British J.Eng. Educ., UK, Vol. 5, No. 1, 2006, pp. 29-42.

[10] Van Zwanenberg, N., Wilkinson, L J., & Anderson, A. , "Felder and Silverman's Index of Learning Styles and Honey and Mumford's Learning Styles Questionnaire: How do they compare and do they predict academic performance?", *Educational Psychology*, Vol. 20, No.3, 2000, pp. 365-381.

[11] McCormick, S., "The Case for Visual Media in Learning", *Syllabus Magazine*, Vol. 13, No. 1, 1999, Syllabus Press.

[12] Montgomery, S. & Groat, L.N., "Student Learning Styles and Their Implications for Teaching", *CRLT Occasional Paper*, Ann Arbor: Center for Research on Learning and Teaching, University of Michigan, 1999.

[13] Nulty, D. & Barrett, M., "Transitions in Students Learning Styles", *Studies in Higher Educ.*, Vol. 21, No. 3, 1996, pp. 333-346.

[14] Zywno, M.S., "Engineering Faculty Teaching Styles and Attitudes toward Student-Centred and Technology-Enabled Teaching Strategies", in *Proc. ASEE Ann. Conf. and Exposition*, Session 1122, Nashville, TN, June 23-25, 2003.

[15] Dunn, R., Giggs, S.A., Olson, J., Beasley, M. & Gorman, B.S., "A meta-analytic validation of the Dunn and Dunn Model of learning preferences", *J. of Educ. Research*, Vol. 88, No. 6, 1995, pp. 353-362.

[16] Gregorc, A.F., "Learning/Teaching Styles: Potent forces behind them", *Educ. Leadership*, Vol. 36, 1979, pp. 234-236.

[17] Kolb, D.A., "Experiential learning: Experience as the source of learning and development", 1984, Englewood Cliffs, NJ: Prentice Hall