GLOBAL VERSUS SEQUENTIAL LEARNING STYLES RELATED TO ATTITUDES ABOUT ONLINE LEARNING

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Abstract

Analysis of student data indicates, according to one definition of learning styles, that global learners respond more favorably to an online, open-ended learning environment than sequential learners. Industrial engineering students were observed before, during, and after engagement in an online forecasting module. Simple ordered logistic regression models of attitudes were found to be consistent functions of the extent to which students are considered to be global versus sequential learners. Furthermore, significance can be observed even when controlling for additional factors such as gender, other learning style dichotomies, preliminary confidence about forecasting knowledge, and problem solving performance.

Keywords: Design, forecasting, learning styles, online learning, ordered logistic regression, problem solving.

Introduction

Problem solving is a critical skill for all engineers, and opportunities for accurate assessment as well as opportunities to measure and improve student performance in this area should benefit students and the profession. Jonassen, *et al.* claimed that work place engineering problems are often ill structured because of multiple and conflicting goals, non-engineering constraints, multiple solution paths and unexpected problems that require extensive collaboration and experiential knowledge [1]. Students must learn how to deal with increasingly complex situations in order to thrive in their future work environments. Creating such a representative environment in the classroom turns out to be a great challenge for engineering educators. One tool created to assist in replicating the ill-structured complex problem solving process and assess performance in such an environment is the Interactive Multi-Media Exercises (IMMEX) tool developed by The Learning Chameleon, Inc. [2, 3]. Using this tool, a complex forecasting scenario was developed and given to a set of undergraduate engineering students to analyze. In this environment students encounter a complex problem in a web-based environment where they are free to choose from a sizable array of information that is available to help them devise a solution to a problem. The approach of using a closed form with many alternatives presented in problem sets provides a kind of guided problem solving, where students learn not only how to produce good results but eventually develop a good process for deriving them. In doing so, students should obtain and make use of the context-appropriate language, an important component of engineering education [4]. Additionally, we gathered attitudinal, learning style and performance data from the pool of junior and senior industrial engineering students that engaged in the online forecasting learning modules in the IMMEX environment.

The IMMEX project, developed by The Learning Chameleon, Inc. hosts an online server system that can deliver problem sets simultaneously to 500 or fewer students. It consists of a database server that records student performance data, and a cluster of load balanced servers that distribute user traffic. IMMEX prototypes typically consist of:

- A prolog or scenario in which the student task is clearly stated,
- Primary and complementary cascading menu items that students access to collect evidentiary data,

- An epilog which summarizes the logic for the solution to the problem investigated,
- A proposed scoring system showing total score and score per menu item, and
- Ideas for potential clones/cases.

No two students are alike. They have different backgrounds, genders, levels of motivation, attitudes about teaching and learning, and responses to specific instructional strategies and practices. Accordingly three major categories of difference have shown significant impact on student learning [5]: 1) Student learning styles, 2) approaches to learning, and 3) intellectual development levels.

Research into learning styles has a history of over thirty years. Reviewing the literature, one quickly discovers that there is a lack of universal agreement on the definition of the various learning styles. Debates exist as to whether an individual's learning style can change over time or remains stable, and whether instructional style should match learning style or not [6]. Zapalska and Brozik claimed that students' learning styles should be incorporated into instructional design, and appropriate teaching strategies that are consistent with students' learning styles are helpful in facilitating learning and improve the achievement of online education [7]. However, learning style theory is not without its critiques. Coffield, *et al.* questioned the validity of thirteen influential models and the value of matching teaching and learning styles by examining the origins of each model and the instruments used to assess learning styles defined by the models [8]. Brown, *et al.* explicitly challenged the usefulness of research into learning styles [9].

With so many different learning style models as well as various teaching methods and technologies apparent in online learning, the relationship between learning styles and online learning becomes very complicated, and learning styles should not be considered as a determining factor for whether or not students should take an online course [10]. In fact using the Learning Style Inventory to measure students' learning styles [11], Yilmaz-Soylu and Akkoyunlu claimed that learning style has no significant effect on student achievement in different learning environments including text based, narration based and computer mediated environments [12].

The model by Kolb introduced four different styles (Converger, Diverger, Assimilator, and Accommodator) that are combinations of four modes (Concrete Experience, Abstract Experience, Reflective Observation, and Active Experimentation) [11]. In a study using Kolb's learning style assessment tool on 285 engineering students over four years, Cagiltay found that Assimilators, make up a large part of the students studied, and Convergers had better performance compared to the Divergers and Accommodators [13]. Cagiltay also claimed that the learning style theory is helpful for teachers' instructional designs and student performance improvement.

Adapted from the Kolb model for specific use by business managers [11], the model by Honey and Munford describes learning styles as Activist, Reflector, Theorist, and Pragmatist with respect to an individual's response to a Learning Style Questionnaire [14]. With a similar structure to the Kolb model [11], the Gregorc Mind Styles™ Model features four different combinations of the two dimensions: Perception (concrete vs. abstract) and Ordering (sequential vs. random) [15]. Each style is seen as a channel through which the mind interacts with the environment and is measured by the Gregorc Style Delineator™, a self-scoring written instrument. Using the Gregorc Style Delineator™ to collect learning style information from 974 students over a four-year period, Ross, *et al.* found sequential learners had significantly better performance than did random learners in two university-level computer applications courses [16].

According to Leite, *et al.* [17], the Visual, Auditory, Reading / Writing, and Kinesthetic (VARK) model of Fleming and Mills is one of the most common and widely used classifications of various learning styles [18]. It divides learners into four groups according to its name via a questionnaire. Zapalska and Brozik stated with respect to the VARK model that [7], "both students and teachers usually exhibit a strong preference for one particular mode [while] they may have a relative weakness or strength in some other modes (p. 328)." According to Moallem [6], the Felder-Silverman Dimensions of Learning Style model seems to be the most appropriate model for learning styles, since it incorporates Jung's theory of psychological types, "combines several dimensions presented in the Myers-Briggs model with the Kolb information processing dimension [11], [and] avoids the complexity of the Dunn and Dunn model (p. 219) [19]." The core idea of the Felder-Silverman model is that instructors should strive for a balance of instructional methods instead of matching the instruction with individual student learning styles. As said by Graf, *et al.*, the major difference between Felder-Silverman's model and other learning style models is that the Felder-Silverman model emphasizes the tendencies indicating learner preferences for certain behaviors without excluding the possibility of acting differently [20]. Most other models simply classify learners into a few groups with less detail. Further, the study by Kuljis and Liu confirmed that the Felder-Silverman learning style model is the most appropriate one [21], "with respect to the application in e-learning and Web-based learning systems (p. 81) [20]."

Based on the Felder-Silverman model, Felder and Soloman developed the Index of Learning Styles (ILS) that is a 44-question, self-scoring instrument assessing preferences on four dimensions of learning:

- Active / Reflective – Active learners tend to understand things by discussion or actually doing something and like group work, while reflective learners tend to think first and prefer working alone.
- Sensing / Intuitive – Sensing learners tend to be more practical, while intuitive learners tend to be more innovative. Sensing learners prefer facts and details, while intuitive learners prefer new concepts and abstractions.
- Visual / Verbal – Visual learners prefer learning with the aid of visual course materials like pictures, diagrams and flow charts, while verbal learners prefer learning with written and spoken explanations.
- Sequential / Global – Sequential learners prefer solving problems through logical steps, while global learners try to get the big picture and learn in big jumps.

Litzinger, *et al.* showed in their study that the ILS "generates data with acceptable levels of internal consistency reliability, and that evidence for its construct validity from both factor analysis and student feedback is strong (p. 316) [22]."

Methods

In our situation two modules of a forecasting problem were created for students to solve (Module1 and Module2). From this part we created six binary independent variables: Attempt1, Attempt2, Complete1, Complete2, Solve1, and Solve2, with each equal to 1 to indicate student behavior, 0 otherwise. For example, Attempt2 = 1 means that student did attempt to solve Module2; Complete1 = 0 means that student did not complete solving Module1; Solve2 = 0 means that student did not solve Module2 correctly. In addition, we defined another two independent variables Time1 and Time2 by recording the time every student spent on each case. Therefore only those who completed a module will have values for Time1 or Time2.

Industrial engineering students in a Production Planning and Control course participated in the problem solving exercise for bonus points toward their final grade. As part of this exercise, students were required to finish three questionnaires. Production Planning and Control is an undergraduate engineering course, which during the period of study had 60 students, 19 females and 41 males, 15 juniors, 44 seniors and 1 graduate student. A significant portion of this course emphasizes forecasting and inventory control, and the problem used in this problem solving exercise focused on forecasting the demand for the next four quarters of a product using up to four years of historical data.

To describe this group we created two binary independent variables, Female and Junior, with Female equal to 1 if that student is a female, 0 otherwise; and Junior equal to 1 if that student is a junior, 0 a senior. (The only graduate student was not taken into consideration, because she did not finish the post questionnaire, the values of which are taken as responses in our analysis.) Three questionnaires were handed out to students, with the first two handed out and answered before solving the IMMEX problems, and the last one after finishing the problem. The first questionnaire is the simple question: "Please indicate how confident you are in your knowledge about forecasting." There are five choices: very confident, confident, neutral, unsure, and very unsure, with a corresponding label from 5 to 1, respectively. For these we defined another variable called Pre. The second questionnaire is the Felder and Soloman ILS. It consists of 44 two-choice questions that indicate learning styles: active or reflective (REF), sensing or intuitive (INT), visual or verbal (VRB), sequential or global (GLO). Here we created another four independent variables called REF, INT, VRB and GLO. Since there are eleven questions for each index of learning style, with a value of either 0 or 1 assigned to the answer, the value of each independent variable ranges from 0 to 11.

The third questionnaire was conducted after students solved the IMMEX problems, and consists of six multi-choice questions as follows:

- Post0. "Please indicate how confident you are in your knowledge about forecasting (very confident, confident, neutral, unsure, or very unsure)," and
- Post1-5. "Please indicate how strongly you disagree or agree with the following statements (strongly agree, agree, neutral, disagree, strongly disagree):"
  - Post1 – "This module helped me to learn more about forecasting."
  - Post2 – "I would like to have more modules like this to help me learn."
  - Post3 – "This module helped me visualize forecasting."
  - Post4 – "This module was relevant to my education."
  - Post5 – "The content of this module was easy to understand."

Altogether we collected useful data from 27 students (with 9 females and 18 males, 7 juniors and 20 seniors) that attempted both modules and also completed the three questionnaires (although only 26 of them completed both modules). Another thing worthy of mention is that only four students correctly solved Module 1 while five students correctly solved Module 2. Our analysis goal was to determine if any relationship existed among the responses and independent variables defined below:

- Using Post0 through Post5 as responses,
- Time1 and Solved1, Time2 and Solved2, Completed1 and Completed2 as three special sets of independent variables, and
- Pre, Female, Junior, REF, INT, VRB and GLO as common independent variables

The ordered logistic regression model is theoretically appropriate to estimate the relationship between an ordinal dependent variable and other independent variables. Since our dependent variable (response) is categorical and ordered (very confident / strongly agree, confident / agree, neutral, unsure / disagree, or very unsure / strongly disagree), we develop a statistical model that estimates the learner's attitudes towards those post questions as a function of the independent variables using ordered logistic regression. In this case, we estimated 6 responses × 3 special sets of independent variables = 18 statistical models. The six responses are Post0 through Post5, and the three sets of independent variables are the following:

- Time1 and Solve1 *(n = 27)*
- Time2 and Solve2 *(same n = 27)*
- Complete1 and Complete2 *(n = 26, number of students that completed both modules)*

From the eighteen models controlling for Pre, Female, Junior, REF, INT, VRB and GLO, we obtained five significant models *(p-value < 0.05).*

- Model1 is Post1 v. Solve2 and Time2 (with significant factors Female, REF and Solve2)
- Model2 is Post2 v. Solve1 and Time1 (with significant factors Pre and GLO)
- Model3 is Post2 v. Complete1 and Complete2 (with significant factors Female and GLO)
- Model4 is Post3 v. Solve2 & Time2 (with Female, VRB & GLO the significant factors)
- Model5 is Post3 v. Complete1 & Complete2 (with significant factors Female, VRB, GLO and Complete1)

For each of the five models we iteratively re-estimated the model using only significant factors until coincidentally there was only one independent variable left in each model. In every case the lone independent variable remaining described an aspect of learning styles. These simple, ordered logistic regression models of online learning attitudes versus learning styles are presented in the next section.

In our case, ordered logistic regression uses maximum likelihood to estimate cut-points K and a basic score that is a simple linear function of some score with respect to learning styles. Let $y = 1$ if the student is very unsure / strongly disagrees with the post questions; let $y = 2$ if the student is unsure / disagrees; let $y = 3$ if the student is neutral; let $y = 4$ if the student is confident / agrees; and let $y = 5$ if the student is very confident / strongly agrees with the post questions. The probability of observing a certain post value is equal to the probability that the functional value is within a range of relevant cut-points:

$$P\,(y = y_1) = P\,(-\infty < b\,x + m \le K_1)$$
$$P\,(y = y_2) = P\,(k_1 < b\,x + m \le K_2)$$
$$\ldots$$
$$P\,(y = y_n) = P\,(k_{n-1} < b\,x + m \le \infty)$$

In keeping with a direct generalization of traditional logistic regression we assume that m has the logistic distribution, and find post value probabilities to be what follows.

$$P\,(y = y_1) = [1 + e\,(-k_1 + b\,x)]^{-1}$$
$$P\,(y = y_2) = [1 + e\,(-k_2 + b\,x)]^{-1} - [1 + e\,(-k_1 + b\,x)]^{-1}$$
$$\ldots$$
$$P\,(y = y_n) = 1 - [1 + e\,(-k_{n-1} + b\,x)]^{-1}$$

Therefore we can get the probability curves for all possible post values based on simple ordered logistic regression models once we find a unique significant independent variable and obtain the appropriate cut-points.

Results

In this section we present details of the significant, simple ordered logistic regression models of online learning attitudes versus learning styles. Model1, which began as Post1 v. Solve2 and Time2 (with significant factors Female, REF, and Solve2). The relevant dataset is composed of students that completed Module2. In this model of Post1 versus only three independent variables Female, REF and Solve2, Solve2 was found to be insignificant and so removed from the analysis. In a model of Post1 versus only the two independent variables Female and REF, Female was found to be insignificant and therefore removed. A simple ordered logistic regression model of Post1 versus REF was not found to be significant.

Thus, based on our sample, we were unable to find an easily interpretable model for the dependent variable Post1, responses to the statement, “This module helped me learn more about forecasting.” The final version of Model2 is for the dependent variable Post2, responses to the statement, “I would like to have more modules like this to help me learn,” as a function of the degree to which Felder and Soloman characterize the respondent as a global (GLO), versus sequential, learner.

Model2, which began as Post2 v. Solve1 and Time1 (with significant factors Pre and GLO) used a dataset composed of students that completed Module1 $(n_2 = 27)$. When analyzing this reduced model of Post2 versus only two independent variables Pre and GLO, Pre was found to no longer be significant. Thus, the final version of Model2, which was found to be significant, is a simple function of GLO based on the data in Table 1.

The ordered logistic regression model based on the data in Table 1 is significant *(p-value = 0.0072)*, and the coefficient $(b = 0.5134729)$ associated with independent variable GLO is also significantly different from zero *(p-value = 0.012)*. Cut-points are the following.

$$K_1 = -1.546179$$
$$K_2 = 1.307543$$
$$K_3 = 3.208958$$

There is not a fourth cut-point, because there is not an observation for the fifth category, “strongly agree.” Table 2 contains the model predicted probabilities associated with empirical combinations of Post2 versus global learning style.

The curves in Figure 1 illustrate the predicted probabilities of the various global learning styles. The various lines, labeled with abbreviations for agree (A), neutral (N), disagree (D), and strongly disagree (SD), represent the responses to the statement, “I would like to have more modules like this to help me learn.”

Table 1. Response to Post2 versus degree to which respondent is a global learner.

	0	1	2	3	4	5	6	7	8	9	10	11
Strongly agree												
Agree	1				1	2		3	1			
Neutral		1	2	1	2	1	2	1				
Disagree			3		4	1						
Strongly disagree	1											

Table 2. Model predicted probabilities of response to Post2 versus global learning style.

	0	1	2	3	4	5	6	7	8
Agree	0.039	0.063	0.101	0.159	0.240	0.345	0.468	0.595	0.711
Neutral	0.174	0.248	0.329	0.399	0.439	0.434	0.387	0.313	0.232
Disagree	0.611	0.576	0.499	0.398	0.295	0.205	0.135	0.086	0.054
Strongly disagree	0.176	0.113	0.071	0.044	0.027	0.016	0.010	0.006	0.003

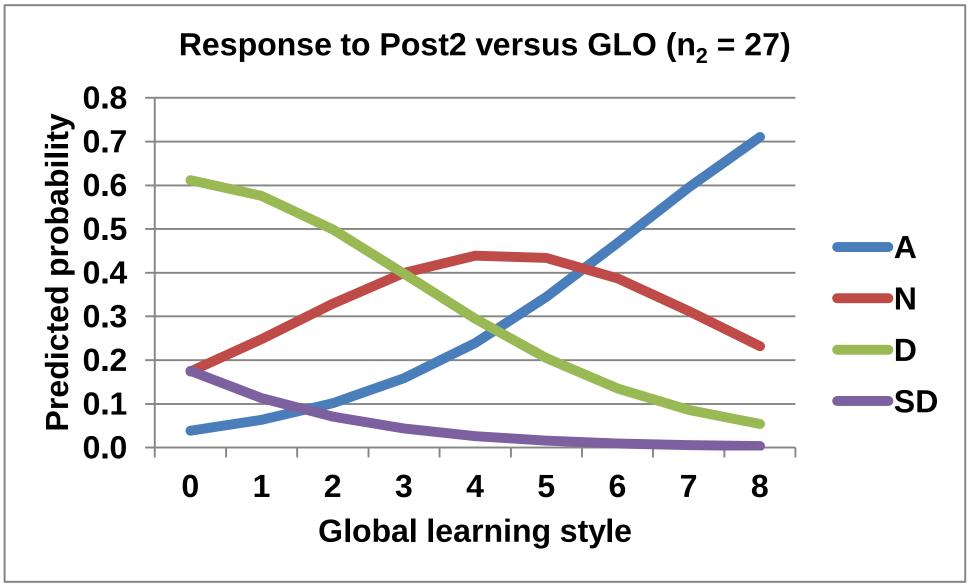

Figure 1. Model predicted probabilities of response to Post2 versus global learning style.

The predicted probabilities illustrated in Figure 1 suggest that, as the student sampled becomes less of a sequential learner and more of a global learner, the student is likely to respond more favorably to the statement, "I would like to have more modules like this to help me learn." In other words, response to the online learning activities was significantly more favorable among the students characterized as more global, versus sequential, learners.

Like Model 2, the final version of Model3 is for the dependent variable Post2, which is a measure of the response to the statement, "I would like to have more modules like this to help me learn," as a function of the degree to which Felder and Soloman characterize the respondent as a global (GLO), versus sequential, learner. Model3, which began as Post2 v. Complete1 and Complete2 (with significant factors Female and GLO) used the dataset composed of only students who completed both modules *(n_3 = 26)*. In this model of Post2 versus a reduced set of two independent variables, Female and GLO, Female was found to be insignificant and therefore removed from the model. Thus, the final version of Model3 which was found to be significant is a simple function of GLO based on the data in Table 3 which is identical to Table 1 except for the one student who did not complete Module2, represented by the explicit zero (0).

The ordered logistic regression model based on the data in Table 3 is significant *(p-value = 0.0046)*, and the coefficient *(b = 0.5532347)* associated with independent variable GLO is also significantly different from zero *(p-value = 0.009)*. Cut-points are the following.

$$K_1 = -1.438864$$
$$K_2 = 1.290148$$
$$K_3 = 3.338705$$

There is not a fourth cut-point, because there is not an observation for the fifth category, "strongly agree." Table 4 contains the model predicted probabilities associated with empirical combinations.

The curves in Figure 2 illustrate the predicted probabilities of the various global learning styles. The various lines, labeled with abbreviations for agree (A), neutral (N), disagree (D), and strongly disagree (SD), represent the responses to the statement, "I would like to have more modules like this to help me learn."

Table 3. Response to Post2 versus degree to which respondent is a global learner.

	0	1	2	3	4	5	6	7	8	9	10	11
Strongly agree												
Agree	1				1	2		3	1			
Neutral		1	2	1	2	1	2	1				
Disagree			3		4	0						
Strongly disagree	1											

Table 4. Model predicted probabilities of response to Post2 versus global learning style.

	0	1	2	3	4	5	6	7	8
Agree	0.034	0.058	0.097	0.157	0.245	0.361	0.495	0.630	0.748
Neutral	0.182	0.266	0.357	0.434	0.471	0.453	0.389	0.299	0.210
Disagree	0.592	0.556	0.473	0.365	0.259	0.171	0.108	0.065	0.039
Strongly disagree	0.192	0.120	0.073	0.043	0.025	0.015	0.009	0.005	0.003

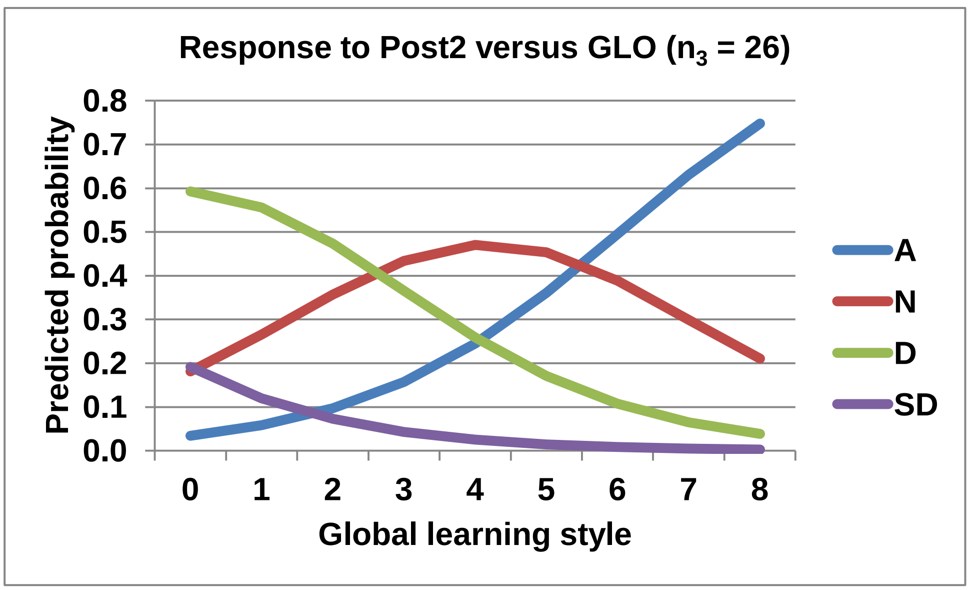

Figure 2. Model predicted probabilities of response to Post2 versus global learning style.

Like Figure 1, the predicted probabilities illustrated in Figure 2 suggest that, as the student sampled becomes less of a sequential learner and more of a global learner, the student is likely to respond more favorably to the statement, “I would like to have more modules like this to help me learn.” In other words response, to the online learning activities was significantly more favorable among the students characterized as more global, versus sequential, learners.

The final version of Model4 is for the dependent variable Post3, which is a measure of the response to the statement, “This module helped me visualize forecasting,” as a function of the degree to which Felder and Soloman characterize the respondent as a global (GLO), versus sequential, learner. Model4, which began as Post3 v. Solve2 and Time2 (with significant factors Female, VRB and GLO) used a dataset composed of students who completed Module2 *(n_4 = 26)*. In this model of Post3 versus the reduced set of three independent variables, Female, VRB, and GLO, Female and VRB were found to be insignificant and therefore removed from the model. Therefore, the final version of Model4, which was found to be significant, is a simple function of GLO based on the data in Table 5.

The ordered logistic regression model based on the data in Table 5 is significant *(p-value = 0.0110)*, and the coefficient *(b = 0.5841927)* associated with independent variable GLO is also significantly different from zero *(p-value = 0.021)*. Cut-points are the following.

$$K_1 = -1.496598$$
$$K_2 = -0.6892257$$
$$K_3 = 0.9966777$$
$$K_4 = 6.166835$$

Table 6 contains the model predicted probabilities associated with empirical combinations.

The curves in Figure 3 illustrate the predicted probabilities of the various global learning styles. The lines, labeled with abbreviations for strongly agree (SA), agree (A), neutral (N), disagree (D), and strongly disagree (SD) represent the responses to the statement, “This model helped me visualize forecasting.” Model predicted probabilities illustrated in Figure 3 suggest that, as the student sampled becomes less of a sequential learner and more of a global learner, the student sampled is likely to respond more favorably to the statement. Expectations about student agreement and strong agreement tend to increase with the extent to which the student can be characterized as a global, versus sequential, learner.

Model5, which began as Post3 v. Complete1 & Complete2 (with Female, VRB, GLO and Complete1 as significant factors) used a dataset originally composed of students that completed both modules *(n_5 = 26)*. When analyzing the model of Post3 versus just the originally significant factors, Female, VRB, GLO and Complete1, the main effects all remain significant. The extent to which a student learner is identified as a global learner positively relates to impressions of the

Table 5. Response to Post3 versus degree to which respondent is a global learner.

	0	1	2	3	4	5	6	7	8	9	10	11
Strongly agree								1				
Agree		1	4		5	3	2	2	1			
Neutral	1		1	1	2							
Disagree						1						
Strongly disagree	1											

Table 6. Model predicted probabilities of response to Post3 versus global learning style.

	0	1	2	3	4	5	6	7	8
Strongly agree	0.002	0.004	0.007	0.012	0.021	0.037	0.065	0.111	0.183
Agree	0.268	0.395	0.536	0.669	0.771	0.835	0.859	0.845	0.792
Neutral	0.396	0.383	0.322	0.239	0.161	0.101	0.060	0.035	0.020
Disagree	0.151	0.108	0.070	0.043	0.025	0.014	0.008	0.005	0.003
Strongly disagree	0.183	0.111	0.065	0.037	0.021	0.021	0.007	0.004	0.002

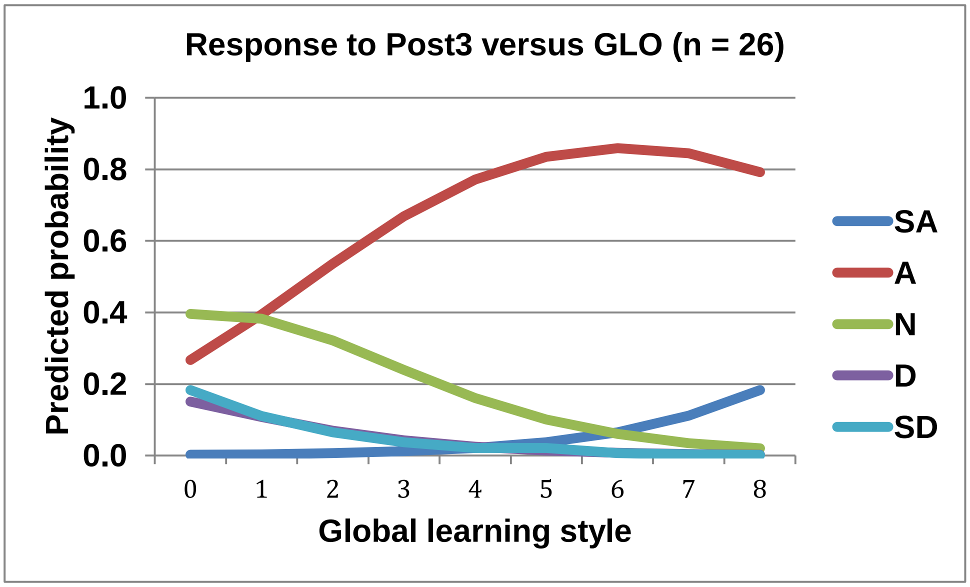

Figure 3. Model predicted probabilities of response to Post3 versus global learning style.

statement, "This module helped me visualize forecasting." This is true now explicitly controlling for gender, verbal versus visual learning style, and whether or not a student completed Module1.

Conclusions

From our analysis, we find that one of Felder-Silverman learning styles – global versus sequential learning – is a significant factor in models of student attitudes toward online learning modules designed to teach forecasting concepts in industrial engineering. In our study, global learners tended to agree with the following statements: "I would like to have more modules like this to help me learn, and this module helped me visualize forecasting." These results are consistent with published descriptions of the learning styles. According to Felder and Soloman sequential learners try to solve problems in logical steps, while global learners prefer to grasp the big picture and learn in large jumps. The open-ended nature of our online learning modules in forecasting would seem to favor global learners. They are not led through logical steps of information gathering and processing. Instead students are encouraged to gather information in their own way and create a personal path, however nonlinear, to a solution.

Also for the case study we created with IMMEX, a good approach to solve the forecasting problem is to look at historical data first (grasp the big picture), and then make intelligent decisions about the appropriate forecasting methodology. A more sequential approach is to iteratively assess a large number of forecasting methods and compare their results, which seems relatively inefficient and undesirable in this case. Further work should consider pedagogic and policy consequences of the research and results described here. Regardless, across learning styles, our results show global versus sequential learners prefer the open-ended case studies made possible with the online learning technology.

Acknowledgements

This work was performed as part of the National Science Foundation sponsored Industry/University Cooperative Research Center for Engineering Logistics and Distribution. The Learning Chameleon, Inc. and the National Science Foundation under its Small Business and Innovative Research support for

I/UCRC programs jointly funded this work. The authors would like to thank Dr. Ron Stevens, John Stallings and Peter Wang for their support in helping us implement the forecasting case study in their IMMEX environment.

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