Learning Styles, Online Content Usage and Exam Performance in a Mixed-Format Introductory Computer Information Systems Course

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Abstract

We investigate the relationship between learning styles, online content usage and exam performance in an undergraduate introductory Computer Information Systems class comprised of both online video tutorials and in-person classes. Our findings suggest that, across students, (1) traditional learning style classification methodologies do not predict behavioral measures of online learning, and (2) working on the online content specifically during allotted class time is positively related to exam performance. Controlling for differences across students, we find (3) accessing content on non-class days (consistency) is positively related to exam performance, while (4) working substantially ahead of the scheduled content pace is negatively related to exam performance.

Keywords: learning styles, online content usage, exam performance, mixed-format teaching

1. INTRODUCTION

The use of online learning systems in higher education and beyond has dramatically increased in recent years (Azarnush et al., 2013). Due to their web-based nature, online learning systems allow for the automatic collection of usage data. This, in turn, offers researchers and educators new opportunities to understand and improve student learning.

Recent technological and methodological advances present an array of techniques that hold the potential to gain deep insights from these data. These advances have led to novel findings in such disparate fields as medicine, marketing, logistics, and education. The field of education is particularly concerned with developing methods for exploring the unique types of data that come from educational settings, and using those methods to better understand students and the settings in which they learn (Baker & Yacef, 2009). The present work aims to bridge nascent literatures, which use such data to predict individual learning styles as well as learning outcomes.

Little is currently known about systematic differences across students in online content usage, and if these differences are associated with particular learning styles and ultimately with exam performance. In particular, one question yet to be addressed is whether traditionally-measured learning styles are useful for predicting online content usage. Early work establishing conceptual models used to define learning styles dates to the mid-1980s, suggesting such conceptualizations may not apply as readily to today's learning environment.

Specifically, the present work aims to investigate the relationship between learning styles and online content usage and the relationship between online content usage and exam performance. The work thus has theoretical implications for learner classification methodologies and practical implications for educators in mixed-format classroom settings.

2. LITERATURE REVIEW

Kolb's (1984) seminal treatise on defining student learning styles gave rise to a literature in the educational field implementing the "Kolb Model" to characterize students and assess their responsiveness to varied educational methods. Since then, new models of learning styles have come into practice, building on the work of Kolb (1984). Recent years have seen an explosion of data related to student use and interaction with learning content via computerized delivery methods, and a corresponding emergence of literature which applies conceptual learning style models to these new sources of information about learners (Khan et al. 2009, among others). The proposed work seeks to add to nascent literature which bridges conceptual models of learning styles (and their relation to learning outcomes) with the wealth of data now available to educators and researchers via new delivery platforms.

The work relates to two distinct strands of literature. The first uses data from web-learning platforms to predict student performance. Baugher et al. (2003) were among the earliest to study this relationship, examining whether total hits or inter-class consistency of hits to a course content web site have any value for predicting student performance in a course supplemented with online activities, finding stronger effects for the latter. Grabe et al. (2005) followed with a similar investigation, finding positive effects of the availability of online materials on both class absence and overall grades. In contrast to these early studies, Abdous et al. (2012) found little relationship between online activity and performance. Romero et al. (2013) use and compare the results of an array of data mining methods to predict student grades based on online usage data.

Studies comprising a second and more recent literature use advanced analytical techniques and detailed web usage information to predict student learning styles. Lu et al. (2007) and Hung and Zhang (2008) are among the first of these, investigating the relationship between learning style measures, online behavior and learning outcomes. More recent studies on the same topic include Ballenger and Garvis (2009), Hung and Crooks (2009) and Bousbia (2010). Clewley et al. (2011) and Azarnoush et al. (2013) use related methods to detect learner styles, and examine how content delivery systems can be adapted dynamically to adjust to individual-user learning types. Recent reviews which more comprehensively detail these and related studies can be found in Romero and Ventura (2007), Baker and Yacef (2009) and, specifically for business-related disciplines, Arbaugh et al. (2009).

Overall, existing studies yield some common conclusions. First, it is important to be aware of, and also detect, student learning styles—especially when using online courses, and that consideration should be given to the diversity of learning styles when designing and developing online learning modules (in terms of content presentation and design features, for example). Second, educational data mining combined with traditional statistical analysis can give a deeper understanding of the determinant of student learning and performance. The current study seeks to build on the work of Lu et al. (2007) and Hung and Zhang (2008) in that we apply data mining techniques to investigate the relationship between learning styles (as measured by a separately-administered survey) and online content usage, and then assess the relationships between online content usage and exam performance.

3. METHODOLOGY

We use a combination of server log files, exam scores, and surveys which were collected over the course of the Spring 2014 semester in three sections of CIS 101 (Introduction to Information Systems) at a mid-sized private university in the northeastern United States. CIS 101 introduces students to various aspects of developing and managing computer information systems and is a required class for all business freshmen. As part of CIS 101, students received three weeks of intensive Microsoft Excel training online (referred to as the Excel Boot Camp). The Excel Boot Camp content is delivered online and consists of 22 lessons, each of which consists of a short video tutorial and an exercise. Although the Excel Boot Camp is delivered online, students were still required to attend class (Mondays, Wednesdays, and Fridays for 50 minutes each). In each class, students were asked to work on the Excel Boot Camp individually. Although the Excel Boot Camp is self-paced, students were required to submit their completed exercises according to a pre-defined schedule (averaging about seven exercises per week).

The web-based nature of the platform allowed us to capture user interaction with the content as recorded in server log files. The log files contain information about each user's online content usage, such as login and logout times, as well as the time spent on each page. Consequently, the log files provide a rich source to quantify various aspects of student online content usage. Specifically, the following behavioral measures were calculated in order to quantify online content usage:

- *time online during class time* (hours spent viewing online content while being in class),
- *consistency* (number of non-class days during which a student visited the online content before the beginning of the exam study period),
- *time online in exam study period* (hours spent viewing online content during the exam study period), and
- *time online working ahead* (hours spent working ahead of the class before the exam study period).

Two weeks after the end of the three-week Excel Boot Camp, students were tested on their knowledge of Microsoft Excel. The exam consisted of 20 multiple-choice questions, most of which require students to download an Excel worksheet and perform analyses in order to derive an answer. All exam questions were directly linked to one of the 22 lessons in the Excel Boot Camp. Given the two-week lag between the completion of the Excel Boot Camp and the exam, students were encouraged to go back and review lessons in the Excel Boot Camp during the exam study period.

At the end of the semester, students were asked to complete a survey on learning styles. The survey was comprised of questions which form the basis for the Index of Learning Styles (Felder & Silverman, 1988; Felder & Spurlin, 2005) and the Kolb Learning Style Inventory (Smith & Kolb, 1986).

The Index of Learning Styles (hereafter "ILS") assesses learning preferences on four dimensions. Each of the four scales consists of 11 items. For each item, students complete a sentence by choosing one of two options representing opposite ends of the dimension. The four dimensions are (see Felder & Spurlin, 2005):

- *sensing* (concrete, practical, oriented toward facts and procedures) or *intuitive* (conceptual, 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 one or two familiar partners), and
- *sequential* (linear thinking process, learn in incremental steps) or *global* (holistic thinking process, learn in large leaps).

The Kolb Learning Style Inventory (hereafter "Kolb LSI") assesses students' preference for perceiving and processing information. It is based on Kolb's experiential learning theory (Kolb, 1985), which posits that how a person perceives information can be classified as concrete experience or abstract conceptualization, and how a person processes information can be classified as active experimentation or reflective observation (Simpson & Du, 2004). The Kolb LSI asks students to rank order four endings for 12 sentences according to how well they think each one fits them. Each of the four endings represents one of the four dimensions in Kolb's experiential learning theory, which can be described as (see Lu et al., 2007):

- *concrete experience* (tends towards peer orientation and benefits most from discussion with fellow learners),
- *abstract conceptualization* (tends to be oriented more towards symbols and learns best in authority-directed, impersonal learning situations, which

emphasized theory and systematic analysis),
- *active experimentation* (tends to be an active, "doing" orientation to learning that relies heavily on experimentation and learns best while engaging in projects), and
- *reflective observation* (tends to rely heavily on careful observation in making judgments).

4. RESULTS

A total of 91 students were enrolled in three sections of CIS 101. All students completed the Excel Boot Camp and the accompanying exam. Of those, 82 (90%) completed the end-of-semester survey on learning styles. As seen in summary statistics presented in Table 1 (see Appendix), students spent far more time online during class time (M = 6.36, SD = 2.42) as they spent online working ahead (M = 1.10, SD = 0.79). On average, students visited the online content on eight of the 15 non-class days before the beginning of the exam study period. During the exam study period, students spent on average less than half an hour accessing the online content (M = 0.28, SD = 0.45).

The correlations between all measures used in this study are presented in Table 2 (see Appendix). With regards to learning styles, we found only small to moderate correlations between the ILS and the Kolb LSI (all $r \leq 0.32$), suggesting that the two instruments measure different aspects of learning styles. The largest correlation is between the active-reflective dimension of the ILS and the active experimentation dimension of the Kolb LSI. This is not surprising, given that both of these dimensions measure a preference for "learning by doing".

There is also substantial variation in the learning styles across students in the class, suggesting that the class composition was not overly skewed in terms of attracting only a certain type (or certain types) of students, as show in Figure 1 (see Appendix).

In order to examine the relationship between learning styles and online content usage, we conducted ordinary least squares regressions of learning style dimensions (both ILS and Kolb LSI) on the various measures of online content usage. Although there is substantial variation in the distribution of the types of students taking the class (Table 1 and Figure 1), the regression results in Table 3 (see Appendix) show that neither of the learning style typologies yields strong predictions of online content usage. Among the learning style measures captured by our survey, only one type has a statistically significant relationship with any of the online content usage measures: a higher score on the "reflective observation" component of the Kolb LSI is associated with a higher likelihood of working ahead of schedule (although the effect is small: β = .035, $p < .05$). This finding suggests that students who are more reflective learners, and thus tend to rely more on careful observation, may be more intrigued to work ahead and explore the content ahead of class than students who are less reflective learners.

We next investigate the relationship between online content usage and exam performance at two levels of aggregation: between students (i.e. across students) and within students (i.e. across lessons controlling for student-level differences). The latter level of aggregation is possible due to the server log data identifying which specific lessons a user was viewing, and for how long, and by linking exam questions to specific lessons we are able to construct a topic level panel. The estimating equation for the between-students regression is the following:

$$(1)\ \boldsymbol{Score_i = \beta_0 + \beta_1 * class\ time\ spent\ online_i + \beta_2 * time\ spent\ online\ during\ exam\ study_i + \beta_3 * consistency_i + \beta_4 * time\ spent\ working\ ahead_i + u_i}$$

where i indexes students, and all regressors are initially measured as described above.

The results of the between-students regression analysis are presented in Table 4 (see Appendix). Across students, time spent online during class time (as opposed to self-study outside of class, as measured in various ways) is the single best predictor of exam performance (β = .72, $p < .01$). In other words, for every hour (which is slightly longer than one class period) that students accessed the online content during class time, their exam performance increased by 0.72 points (out of 20, equivalent to 3.6 percentage points). This suggests that working on online content during class time is more effective than working on online content outside of class time. Given that this measure in essence captures class attendance, this finding suggests that irrespective or student-level differences, the single most important factor influencing exam performance is coming to class and working on the assigned online content. Although this finding might not seem particularly novel at first, we believe this points to the importance of blended learning strategies that combine online and in-person classes.

The results of the between-students regression analysis paint a different, more nuanced picture. The estimating equation is:

(2) $\boldsymbol{Score_{i,j}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} * \boldsymbol{class\ time\ spent\ online_{i,j}} + \boldsymbol{\beta_2} * \boldsymbol{time\ spent\ online\ during\ exam\ study_{i,j}} + \boldsymbol{\beta_3} * \boldsymbol{consistency_{i,j}} + \boldsymbol{\beta_4} * \boldsymbol{time\ spent\ working\ ahead_{i,j}} + \Gamma * \mathrm{X}_j + \boldsymbol{u_{i,j}}$

where *i* still indexes students, *j* indexes lessons, and X_j is a vector of student fixed effects.

Table 5 (see Appendix) contains the results of the estimation of equation (2). When accounting for individual differences, time spent online during class time is no longer a significant predictor for exam performance (β = .0004, p > .05). In contrast, we found that consistency, as measured by the number of non-class days during which a student used the online content, is significantly related to exam performance (β = .073, p < .001). In other words, for every non-class day that students accessed the online content for a particular lesson, their chance of correctly answering the exam question relating to that lesson increased by 7.3 percentage points. Interestingly, the significant negative coefficient for time spent online working ahead of the class (β = -0.11, p < .01) suggests that working ahead decreases students' exam performance. Specifically, this suggests that for every hour spent working ahead of the class, students' chance of answering the exam question relating to the lesson that they should be working on decreased by 11 percentage points.

5. CONCLUSIONS

The aim of this study was to understand the relationships between learning styles, online content usage, and exam performance. We analyzed a unique dataset that gave us rich information on student access patterns of online content that was part of a hybrid university course. Our findings suggest that (1) traditional typologies of learning styles may not accurately classify the different ways students have of interacting with online content, (2) the number of hours spent working on the online content during class time is positively related to exam performance, (3) the number of non-class days during which students access online content is positively related to exam performance, and (4) the number of hours that students work ahead of the class is negatively related to exam performance. Based on these empirical findings, one can deduce three prescriptive guidelines for instructors using online content in their classes: (1) ensure that students work on the online content during class, (2) encourage students to review online content between classes, (3) discourage students from working ahead of the class. These suggestions should help students make the best use of the online content and improve exam performance when delivering content in a hybrid format.

There are a few caveats to the analysis. Specifically, a relatively small sample from a private university in the Northeastern US is probably not representative of the general undergraduate student population. Also, the hybrid class format of combining video-based tutorials with in-person class meetings is unique, which might limit the applicability of our findings to traditional in-person or purely online classes. Lastly, we collected the survey of learning styles at the end of the semester. It is possible, though we believe unlikely, that the experience of the Excel Boot Camp had an effect on students' responses to the survey.

This study adds to an emerging literature using large datasets that capture detailed information on student interaction with educational content to detect patterns of content usage and predict learning outcomes. There are several directions in which future work in this area can go. The first is to use such data collection for semester-long classes, which will provide richer variation to use in classifying student interaction with learning materials. Another will build on this type of data to generate new learning style typologies that are more suited to online learning behaviors.

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Appendix: Tables and Figures

Table 1: Summary statistics of online content usage, learning styles and exam performance

	mean	sd	median	min	max	N
by student:						
time online during classtime (hours)	6.36	2.42	5.89	2.07	13.35	91
consistency: non-class days visiting content	8.02	2.58	8	1	15	91
time online in exam study period (hours)	0.28	0.45	0.00	0.00	2.06	91
time online working ahead (hours)	1.10	0.79	0.85	0.13	3.65	91
Active-Reflective (ILS)	-1.37	3.98	-1	-9	9	82
Sensing-Intuitive (ILS)	-2.35	5.64	-3	-11	11	82
Visual-Verbal (ILS)	-4.17	4.65	-5	-11	9	82
Sequential-Global (ILS)	-1.78	3.51	-3	-9	9	82
Abstract Conceptualization (Kolb)	31.00	5.73	32	15	44	82
Active Experimentation (Kolb)	31.85	8.40	33	16	48	82
Concrete Experience (Kolb)	28.77	7.89	29	13	46	82
Reflective Observation (Kolb)	28.28	6.94	27	14	48	82
Exam score (# correct out of 20)	16.18	3.40	17	5	20	91
by student-lesson:						
time viewing lesson content during classtime (hours)	0.32	0.30	0.26	0.00	2.04	819
consistency: non-class days visiting lesson content	1.04	0.71	1	0	4	819
time viewing lesson content in exam study period (hours)	0.02	0.06	0.00	0.00	0.54	819
time viewing lesson content working ahead (hours)	0.11	0.24	0.00	0.00	1.96	819
% correct of questions asked on lesson content	0.79	0.35	1	0	1	819
across individual pageviews:						
time on page (individual view; in seconds)	762.99	769.21	569	60	7190	2829

Notes: Table presents summary statistics of online content use, learning styles and exam performance at various levels of aggregation.

Table 2: Pairwise correlations of online content usage, learning styles and exam performance

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Exam score	1												
2. time online during classtime (hours)	0.26	1											
3. time online in exam study period (hours)	0.17	0.16	1										
4. consistency: non-class days visiting content	0	-0.3	0.2	1									
5. time online working ahead (hours)	0.05	0.01	0.09	0.21	1								
6. Active-Reflective (ILS)	-0.03	-0.05	-0.07	-0.07	-0.15	1							
7. Sensing-Intuitive (ILS)	-0.1	-0.12	-0.01	-0.03	0.23	-0.29	1						
8. Visual-Verbal (ILS)	0.06	0.05	0.21	0.15	0.02	0.14	-0.23	1					
9. Sequential-Global (ILS)	-0.03	-0.2	0.05	0.05	0.2	-0.01	0.21	-0.05	1				
10. Abstract Conceptualization (Kolb)	-0.05	-0.06	-0.04	-0.08	0.01	-0.06	-0.18	0.16	-0.16	1			
11. Active Experimentation (Kolb)	-0.15	0.06	-0.09	-0.12	-0.09	0.32	0.04	-0.01	-0.1	-0.14	1		
12. Concrete Experience (Kolb)	0.09	0.01	-0.01	0.06	-0.12	-0.04	-0.17	0.03	0.11	-0.39	-0.53	1	
13. Reflective Observation (Kolb)	0.14	-0.02	0.16	0.13	0.24	-0.28	0.3	-0.18	0.15	-0.22	-0.5	-0.17	1

Notes: Table presents pairwise Pearson correlation coefficients across combinations of student-level measures.

Table 3: Predicting online content usage with learning styles, OLS regression results, student-level variation

Dependent variable	time online during classtime (hours)	time online in exam study period (hours)	consistency: non-class days visiting content	time online working ahead (hours)
Panel A: Using ILS				
Active-Reflective (ILS)	-0.024	-0.011	-0.064	-0.022
	(0.04)	(0.01)	(0.07)	(0.02)
Sensing-Intuitive (ILS)	-0.022	0.0001	-0.015	0.026
	(0.03)	(0.01)	(0.05)	(0.02)
Visual-Verbal (ILS)	0.007	0.020*	0.084	0.014
	(0.03)	(0.01)	(0.06)	(0.02)
Sequential-Global (ILS)	-0.06	0.007	0.045	0.037
	(0.04)	(0.01)	(0.08)	(0.03)
Constant	1.621***	0.350***	8.541***	1.275***
	(0.21)	(0.07)	(0.44)	(0.14)
Observations	82	82	82	82
R2	0.052	0.057	0.036	0.094
Panel B: Using Kolb Learning Styles				
Abstract Conceptualization (Kolb)	-0.012	-0.001	-0.036	0.012
	(0.03)	(0.01)	(0.05)	(0.02)
Active Experimentation (Kolb)	0.006	-0.001	-0.028	0.007
	(0.02)	(0.01)	(0.04)	(0.01)
Reflective Observation (Kolb)	-0.003	0.009	0.021	0.035**
	(0.02)	(0.01)	(0.05)	(0.02)
Constant	2.059	0.084	9.646***	-0.484
	(1.63)	(0.55)	(3.25)	(1.03)
Observations	81	82	82	82
R2	0.006	0.026	0.026	0.068

Notes: Table presents coefficients from a linear regression estimating various aspects of online behavior. Standard errors in parentheses. Significance levels indicated by * .10, ** .05, ***.01.

Table 4: Predicting exam scores with online content usage, OLS regression results, student-level variation

	(1)	**(2)**	**(3)**	**(4)**
time online during classtime (hours)	0.720**	0.450**	0.616**	0.412**
	(0.31)	(0.18)	(0.31)	(0.18)
time online in exam study period (hours)	0.846	0.11	0.869	0.104
	(0.82)	(0.10)	(0.80)	(0.10)
consistency: non-class days visiting content	0.062	0.067	-0.051	-0.039
	(0.15)	(0.16)	(0.15)	(0.16)
time online working ahead (hours)	0.131	0.191	0.099	0.092
	(0.46)	(0.52)	(0.45)	(0.52)
Constant	14.021***	10.055**	15.252***	12.151***
	(1.47)	(4.48)	(1.53)	(4.55)
Observations	91	91	88	88
R2	0.089	0.089	0.082	0.087

Notes: Dependent variable exam score. Table presents coefficients from a linear regression estimating exam scores with measures of online behavior. Columns 3 and 4 exclude a small number of students with outlier values in online use measures. Columns 2 and 4 estimate the specification using natural logs of the online time measures. Standard errors in parentheses. Significance levels indicated by * .10, ** .05, ***.01.

Table 5: Predicting exam scores with online content usage, OLS regression results, student-lesson variation

	(1)	(2)
time online during classtime (hours)	0.0004	0.0003
spent on lesson	(0.10)	(0.01)
time online in exam study period (hours)	0.004	0.007
spent on lesson	(0.25)	(0.01)
consistency: non-class days visiting lesson	0.073***	0.066**
	(0.02)	(0.03)
time online working ahead (hours)	-0.110**	-0.007*
spent on lesson	(0.05)	(0.00)
Student fixed effects	Y	Y
Observations	819	819
$R2$	0.886	0.886

Notes: Dependent variable: Percentage correct of questions pertaining to lesson. Table presents coefficients from a linear regression estimating question scores across lessons and students. Column 2 estimates the specification using natural logs of the online time measures. Standard errors in parentheses. Significance levels indicated by * .10, ** .05, ***.01.

Figure 1: Histogram of learning styles across students