

INFORMATION SYSTEMS EDUCATION JOURNAL

In this issue:

- 4. Business Analytics in Practice and in Education: A Competency-based Perspective**
Stanislav Mamonov, Montclair State University
Ram Misra, Montclair State University
Rashmi Jain, Montclair State University
- 14. Learning Styles, Online Content Usage and Exam Performance in a Mixed-Format Introductory Computer Information Systems Course**
Guido Lang, Quinnipiac University
Stephen D. O'Connell, CUNY Graduate School and University Center
- 23. Evaluating Business Intelligence / Business Analytics Software for Use in the Information Systems Curriculum**
Gary Alan Davis, Robert Morris University
Charles R. Woratschek, Robert Morris University
- 30. T0: Discrete Math and Programming Logic Topics as a Hybrid Alternative to CS0**
Nancy L. Martin, Southern Illinois University
- 45. A Proposed Concentration Curriculum Design for Big Data Analytics for Information Systems Students**
John C. Molluzzo, Pace University
James P. Lawler, Pace University
- 58. A Design Quality Learning Unit in OO Modeling Bridging the Engineer and the Artist**
Leslie J. Waguespack, Bentley University

The **Information Systems Education Journal** (ISEDJ) is a double-blind peer-reviewed academic journal published by **EDSIG**, the Education Special Interest Group of AITP, the Association of Information Technology Professionals (Chicago, Illinois). Publishing frequency is six times per year. The first year of publication is 2003.

ISEDJ is published online (<http://isedj.org>). Our sister publication, the Proceedings of EDSIG (<http://www.edsigcon.org>) features all papers, panels, workshops, and presentations from the conference.

The journal acceptance review process involves a minimum of three double-blind peer reviews, where both the reviewer is not aware of the identities of the authors and the authors are not aware of the identities of the reviewers. The initial reviews happen before the conference. At that point papers are divided into award papers (top 15%), other journal papers (top 30%), unsettled papers, and non-journal papers. The unsettled papers are subjected to a second round of blind peer review to establish whether they will be accepted to the journal or not. Those papers that are deemed of sufficient quality are accepted for publication in the ISEDJ journal. Currently the target acceptance rate for the journal is under 40%.

Information Systems Education Journal is pleased to be listed in the 1st Edition of Cabell's Directory of Publishing Opportunities in Educational Technology and Library Science, in both the electronic and printed editions. Questions should be addressed to the editor at editor@isedj.org or the publisher at publisher@isedj.org.

2015 AITP Education Special Interest Group (EDSIG) Board of Directors

Scott Hunsinger
Appalachian State Univ
President

Jeffrey Babb
West Texas A&M
Vice President

Wendy Ceccucci
Quinnipiac University
President – 2013-2014

Eric Breimer
Siena College
Director

Nita Brooks
Middle Tennessee State Univ
Director

Tom Janicki
U North Carolina Wilmington
Director

Muhammed Miah
Southern Univ New Orleans
Director

James Pomykalski
Susquehanna University
Director

Anthony Serapiglia
St. Vincent College
Director

Leslie J. Waguespack Jr
Bentley University
Director

Peter Wu
Robert Morris University
Director

Lee Freeman
Univ. of Michigan - Dearborn
JISE Editor

Copyright © 2015 by the Education Special Interest Group (EDSIG) of the Association of Information Technology Professionals (AITP). Permission to make digital or hard copies of all or part of this journal for personal or classroom use is granted without fee provided that the copies are not made or distributed for profit or commercial use. All copies must bear this notice and full citation. Permission from the Editor is required to post to servers, redistribute to lists, or utilize in a for-profit or commercial use. Permission requests should be sent to Nita Brooks, Editor, editor@isedj.org.

INFORMATION SYSTEMS EDUCATION JOURNAL

Editors

Nita Brooks
Senior Editor
Middle Tennessee
State University

Thomas Janicki
Publisher
University of North Carolina
Wilmington

Donald Colton
Emeritus Editor
Brigham Young University
Hawaii

Jeffry Babb
Associate Editor
West Texas A&M
University

Wendy Ceccucci
Associate Editor
Quinnipiac University

Melinda Korzaan
Associate Editor
Middle Tennessee
State University

George Nezelek
Associate Editor
Univ of North Carolina Wilmington

Samuel Sambasivam
Associate Editor
Azusa Pacific University

Anthony Serapiglia
Teaching Cases Co-Editor
St. Vincent College

Lawrence Cameron
Teaching Cases Co-Editor
University of Montana

ISEDJ Editorial Board

Samuel Abraham
Siena Heights University

James Lawler
Pace University

Alan Peslak
Penn State University

Teko Jan Bekkering
Northeastern State University

Michelle Louch
Duquesne University

Bruce Saulnier
Quinnipiac University

Gerald DeHondt II

Cynthia Martincic
Saint Vincent College

Li-Jen Shannon
Sam Houston State University

Janet Helwig
Dominican University

Muhammed Miah
Southern Univ at New Orleans

Karthikeyan Umapathy
University of North Florida

Scott Hunsinger
Appalachian State University

Marianne Murphy
North Carolina Central University

Bruce White
Quinnipiac University

Mark Jones
Lock Haven University

Peter Y. Wu
Robert Morris University.

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

Guido Lang
guido.lang@quinnipiac.edu
Quinnipiac University
Hamden, CT 06518

Stephen D. O'Connell
soconnell@gc.cuny.edu
CUNY Graduate School and University Center
New York, NY 10035

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: $\beta = .035$, $p < .05$). 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:

$$(1) \text{Score}_i = \beta_0 + \beta_1 * \text{class time spent online}_i + \beta_2 * \text{time spent online during exam study}_i + \beta_3 * \text{consistency}_i + \beta_4 * \text{time spent working ahead}_i + u_i$$

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 ($\beta = .72$, $p < .01$). 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 of 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:

$$(2) \text{ Score}_{i,j} = \beta_0 + \beta_1 * \text{class time spent online}_{i,j} + \beta_2 * \text{time spent online during exam study}_{i,j} + \beta_3 * \text{consistency}_{i,j} + \beta_4 * \text{time spent working ahead}_{i,j} + \Gamma * X_j + u_{i,j}$$

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 ($\beta = .0004, p > .05$). 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 ($\beta = .073, p < .001$). 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 ($\beta = -0.11, p < .01$) 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.

6. REFERENCES

- Abdous, M., He, W. & Yen, C.-J. (2012). Using Data Mining for Predicting Relationships between Online Question Theme and Final Grade. *Educational Technology & Society*, 15(3), 77-88.
- Arbaugh, J.B. et al. (2009). Research in online and blended learning in the business

- disciplines: Key findings and possible future directions. *The Internet and Higher Education*, 12(2), 71–87.
- Azarnoush, B. et al. (2013). Toward a Framework for Learner Segmentation. *Journal of Educational Data Mining*, 5(2), 102–126.
- Baker, R.S.J.D. & Yacef, K. (2009). The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining*, 1(1), 3–16.
- Ballenger, R.M. & Garvis, D.M. (2009). Student Usage of Instructional Technologies: Differences in Online Learning Styles. *Proceedings of the Information Systems Education Conference*, 1–19.
- Baugher, D., Varanelli, A. & Weisbord, E. (2003). Student Hits in an Internet-Supported Course: How Can Instructors Use Them and What Do They Mean? *Decision Sciences Journal of Innovative Education*, 1(2), 159–179.
- Berkhin, P. (2006). A Survey of Clustering Data Mining Techniques. In Kogan, Jacob, Nicholas, Charles, & Teboulle, Marc (Eds.), *Grouping Multidimensional Data*, 25–71, Springer: New York.
- Bousbia, N. et al. (2010). Analysing the Relationship between Learning Styles and Navigation Behaviour in Web-Based Educational System. *Knowledge Management & E-Learning: An International Journal*, 2(4), 400–421.
- Clewley, N., Chen, S.Y. & Liu, X. (2011). Mining Learning Preferences in Web-based Instruction: Holists vs. Serialists. *Educational Technology & Society*, 14(4), 266–277.
- Felder, R. & Silverman, L. K. (1988). Learning and Teaching Styles in Engineering Education" *Engineering Education*, 78(7), 674–681.
- Felder, R. & Spurlin, J. (2005). Applications, Reliability, and Validity of the Index of Learning Styles. *International Journal of Engineering Education*, 21(1), 103–112.
- Grabe, M., Christopherson, K. & Douglas, J. (2005). Providing Introductory Psychology Students Access to Online Lecture Notes: The Relationship of Note Use to Performance and Class Attendance. *Journal of Educational Technology Systems*, 33(3), 295–308.
- Hung, J. & Zhang, K. (2008). Revealing Online Learning Behaviors and Activity Patterns and Making Predictions with Data Mining Techniques in Online Teaching. *MERLOT Journal of Online Learning and Teaching*, 4(4), 426–437.
- Hung, J.-L. & Crooks, S.M. (2009). Examining Online Learning Patterns with Data Mining Techniques in Peer-Moderated and Teacher-Moderated Courses. *Journal of Educational Computing Research*, 40(2), 183–210.
- Khan, F.A. et al. (2009). Integrated Approach for the Detection of Learning Styles & Affective States. In *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications*. 753–761.
- Kolb, David (1984). *Experiential learning: Experience as the source of learning and development*. Englewood Cliffs, NJ: Prentice-Hall.
- Lu, H. et al. (2007). The Relationship of Kolb Learning Styles, Online Learning Behaviors and Learning Outcomes. *Educational Technology & Society*, 10(4), 187–196.
- Romero, C. & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications*, 33(1), 135–146. Available at: <http://linkinghub.elsevier.com/retrieve/pii/S0957417406001266> [Accessed March 21, 2014].
- Romero, C. et al. (2013). Web usage mining for predicting final marks of students that use Moodle courses. *Computer Applications in Engineering Education*, 21(1), 135–146. Available at: <http://doi.wiley.com/10.1002/cae.20456> [Accessed March 21, 2014].
- Smith, D. M., & Kolb, D. A. (1986). *Learning Style Inventory: User's guide*, Boston: McBer & Company.

Editor's Note: This paper was selected for inclusion in the journal as an ISECON 2014 Distinguished Paper. The acceptance rate is typically 7% for this category of paper based on blind reviews from six or more peers including three or more former best papers authors who did not submit a paper in 2014.

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 (0.04)	-0.011 (0.01)	-0.064 (0.07)	-0.022 (0.02)
Sensing-Intuitive (ILS)	-0.022 (0.03)	0.0001 (0.01)	-0.015 (0.05)	0.026 (0.02)
Visual-Verbal (ILS)	0.007 (0.03)	0.020* (0.01)	0.084 (0.06)	0.014 (0.02)
Sequential-Global (ILS)	-0.06 (0.04)	0.007 (0.01)	0.045 (0.08)	0.037 (0.03)
Constant	1.621*** (0.21)	0.350*** (0.07)	8.541*** (0.44)	1.275*** (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 (0.03)	-0.001 (0.01)	-0.036 (0.05)	0.012 (0.02)
Active Experimentation (Kolb)	0.006 (0.02)	-0.001 (0.01)	-0.028 (0.04)	0.007 (0.01)
Reflective Observation (Kolb)	-0.003 (0.02)	0.009 (0.01)	0.021 (0.05)	0.035** (0.02)
Constant	2.059 (1.63)	0.084 (0.55)	9.646*** (3.25)	-0.484 (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** (0.31)	0.450** (0.18)	0.616** (0.31)	0.412** (0.18)
time online in exam study period (hours)	0.846 (0.82)	0.11 (0.10)	0.869 (0.80)	0.104 (0.10)
consistency: non-class days visiting content	0.062 (0.15)	0.067 (0.16)	-0.051 (0.15)	-0.039 (0.16)
time online working ahead (hours)	0.131 (0.46)	0.191 (0.52)	0.099 (0.45)	0.092 (0.52)
Constant	14.021*** (1.47)	10.055** (4.48)	15.252*** (1.53)	12.151*** (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) spent on lesson	0.0004 (0.10)	0.0003 (0.01)
time online in exam study period (hours) spent on lesson	0.004 (0.25)	0.007 (0.01)
consistency: non-class days visiting lesson	0.073*** (0.02)	0.066** (0.03)
time online working ahead (hours) spent on lesson	-0.110** (0.05)	-0.007* (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

