

Evidence-Based Online Course Development Practices Using Three Years of Incoming Student Data

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Knowledge of university students' reading speed and learning style preferences allows online course designers to more effectively meet the academic needs of all learners. The present study utilizes three years of incoming student data ($N = 1,776$) from a mid-sized online Christian university to determine whether students' average online reading speed and learning style preferences differ significantly between declared majors. Results showed that English majors had a faster on-screen reading time than business and psychology majors. Significant between-major differences were also detected for five of the seven learning style preferences. Implications for course designers are discussed.

Keywords: learning styles, online education, higher education, course development

Introduction

Online course delivery presents new challenges for those seeking to effectively meet the academic needs of all students. Since all or most of the student engagement time takes place outside of the classroom, it is much more difficult for online course designers to effectively estimate how long it will take students to complete a given learning activity. Specifically, it is unclear if page per minute (PPM) reading speed estimates should be uniform across academic majors.¹ Furthermore, in comparison with traditional face-to-face instruction, online course designs tend to favor solitary learning with fewer social activities in asynchronous course developments. Some course designers have suggested that activities favoring a variety of learning style preferences be incorporated into all online course designs in order to maximize student engagement. However, it is unknown whether students' learning style preferences are the same across majors.

The United States (U.S.) Department of Education (2011) defines a credit hour as "a unit of measure that gives value to the level of instruction, academic rigor, and time requirements for course taken at an educational institution" (para. 6). In an online course delivery environment, the course time requirements are generally measured in "student engagement time," described by Savage and Savage (2010) as "the amount of time students spend focused on the educational objectives" (p. 82). In order to meet credit hour requirements, online course designers produce estimates of how long it will take the average student to complete each assignment.

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¹ In the United States and Canada, a major concentration or academic major is the academic discipline to which an undergraduate student formally commits (Rudolph, 1977). An academic major is formally declared by the student by the end of the student's second academic year.

Since reading assignments constitute a significant portion of students' engagement time in an online class, inaccurate PPM guidelines could result in radical misestimates of the time it will take students to complete these assignments. While generating local estimates based on incoming student reading data may solve this problem, it may not be safe to assume that English majors, for example, have the same average reading speed as psychology majors. Therefore, the present study examines a void in the literature by determining whether students' average online reading speed differs significantly between declared majors.

The combination of effective planning and strategic design is the necessary preparation for students to thrive in any environment (Chitanana, 2012). A major report from the U.S. Department of Education (2010) concluded that online course delivery models are most effective when they promote interactive learning or personal engagement with the course materials at deeper levels and over a longer period of time. Some online course designers have utilized theories and research related to multiple intelligences and differences in student learning styles in order to present material in a way that will effectively engage a variety of learners (Gardner & Hatch, 1989; Wang, Wang, Wang, & Huang, 2006). For example, in order to better engage students who prefer to learn in a social environment, a course designer may incorporate an assignment that requires them to interview a member of their chosen profession. However, some preliminary research suggests that learning style preferences may actually vary between academic majors (Cano, 1999). For example, English majors may actually prefer the solitary learning activities commonly associated with online learning, while communications majors may feel a strong desire for more face-to-face interaction. If this is the case, it would not be appropriate for course designers to adopt the same guidelines for all classes. Therefore, the present study seeks to extend the literature by determining whether students' learning style preferences differ significantly between declared majors.

Method

Participants

Data were collected from the online division of a mid-sized private Christian university in Southern California. At the time of the study, the online division housed approximately 1,700 online students while also offering courses to an additional 1,500 traditional students. Participants consisted of online and professional undergraduate students enrolling during three different academic years. Data were available for 400 students in Year 1, 796 students in Year 2, and 580 students in Year 3. Among these students, there were 19 different declared majors: accounting, business, Christian studies, communications, computer information technology, criminal justice, early childhood studies, English, graphic design, interdisciplinary studies, kinesiology, liberal studies, marketing, organizational leadership, political science, psychology, public administration, public relations, and sociology. The gender and ethnic makeup was similar across years. In Year 1, 71% of the students were female. Forty-three percent of the students were Caucasian, 30% were Hispanic or Latino, 14% were African-American, and 2% were Asian. Student ages ranged from 18 to over 60, with the highest proportion of students (30%) falling between the ages of 23 and 27. Ages were approximately normally distributed with a slight positive skew.

Measures

After enrolling in the university, students completed a battery of commercially provided online tests designed to assess their level of preparedness for online learning. Portions of this incoming student data, as well

as information about each student's declared major, were used in this study.

Academic major. Students declared an academic major upon enrollment. Students with no declared major were omitted from the study.

Online reading speed. Students read a one-page on-screen passage about the origins of the contact lens and answered 10 reading recall questions. The website timed how long it took the student to read the passage, and the student's online reading speed was calculated and reported in words per minute (WPM). Among students in Year 1, WPM scores had a surprisingly high mean and contained an unexpectedly large amount of variability ($M = 352.81$; $SD = 1,521.12$). WPM scores ranged from 38 to an implausible 24,840.

After consulting with the authors of the assessment, it was concluded that the students with unrealistically high reading speeds did not actually read the passage but rather clicked through the text as quickly as possible in order to get straight to the recall questions. In an attempt to filter out these students, those who received a failing score on the recall task (with a score below 70%) were removed from the data set. Even after the removal of additional outliers, the distribution continued to exhibit significant positive skewness, which is known to reduce statistical power when the sample size between groups is imbalanced. Therefore, a logarithmic transformation was conducted, thus, normalizing the reading speed distributions for both years.

Learning style preference. The learning style inventory was based on Gardner's (1983) theory of multiple intelligences, with items adapted from related inventories used to assess student abilities in these seven intelligence areas (e.g., Bordelon & Banbury, 2005). Students responded to 35 statements, each indicating one of seven different learning style preferences: aural (e.g., "Jingles, themes, or parts of songs pop into your head at random"), logical (e.g., "You like logic games and brainteasers. You like chess and other strategy games"), physical (e.g., "You love sports and exercise"), social (e.g., "You like playing games with others, such as cards and board games"), solitary (e.g., "You have a personal interest or hobby that you like to do alone"), verbal (e.g., "You like crosswords, playing scrabble, and word games"), and visual (e.g., "You draw well, and you find yourself drawing or doodling on a notepad when thinking"). Response options included: "The statement is nothing like me," "The statement is partially like me," and "The statement is very much like me." Raw scores were computed for each of the seven preference categories, with scores ranging from 0 to 10.

Results

Research Question 1: Does Students' Average Online Reading Speed Differ Significantly Between Declared Majors?

In order to answer our first research question, exploratory analyses were conducted with the first year's incoming student data. Confirmatory analyses were conducted with subsequently obtained data.

Exploratory analyses. After removing students with missing data, failing scores on the reading recall task, or implausibly high WPM scores, 290 students remained in Year 1. English majors contained the highest observed transformed mean (corresponding to a raw score of 191 WPM), while business and psychology majors appeared to be the slowest readers (corresponding to raw scores of 153 WPM and 154 WPM respectively). A one-way analysis of variance (ANOVA) found no significant between-major differences ($F_{(10, 279)} = 1.00$; $p = 0.45$). However, a series of exploratory post-hoc *t*-tests were conducted in order to investigate potential bi-group differences. Bonferroni correction was not applied because the tests were exploratory in nature and because this would have inflated Type II error to an unacceptable level due to the large number of comparisons under study. Among these exploratory post-hoc analyses, two significant

comparisons emerged. English majors were significantly faster readers than both business majors ($t(69) = 2.58$; $p < 0.05$) and psychology majors ($t(61) = 2.09$; $p < 0.05$). These corresponded to a substantively significant raw score difference of 38 WPM and 37 WPM respectively (or roughly 0.60 standard deviations).

Confirmatory analyses. Year 2 students with missing data, failing recall scores, or implausibly high WPM scores were removed from the analysis, resulting in a reduced sample size of 542. Mean standardized transformed WPM scores across majors in Year 2 are illustrated in Figure 1. As expected, English majors appeared to have the fastest reading time (corresponding to a raw score of 229 WPM). Psychology and business majors were among the slowest readers, both with raw scores corresponding to 159 WPM.

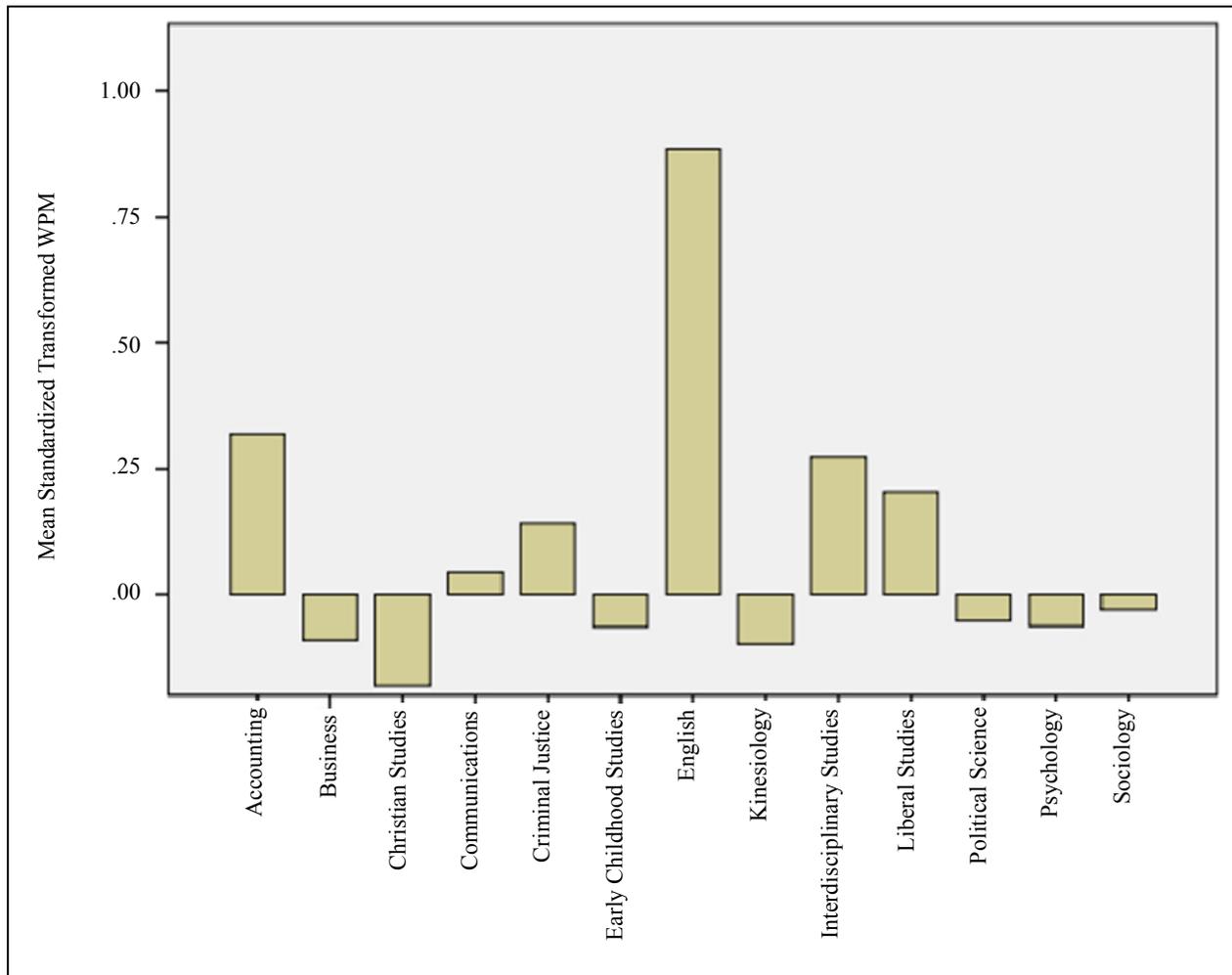


Figure 1. Mean standardized transformed online reading speed (WPM) scores by declared academic major among Year 2 students. English majors read significantly faster than business majors and psychology majors.

Two *a priori* independent samples *t*-tests were conducted to determine whether the differences observed in Year 1 would persist in Year 2. The first test confirmed that, as expected, English majors were statistically significantly faster readers than business majors ($t(216) = 3.16$; $p < 0.01$). Likewise, the second test confirmed that English majors were also significantly faster readers than psychology majors ($t(65) = 2.91$; $p < 0.01$). Moreover, these differences were substantively significant, with English majors reading, on average, 70 WPM faster than both business and psychology majors (roughly equivalent to a full standard deviation). Additional

exploratory post-hoc comparisons were generated, with uncorrected *t*-tests demonstrating a significant advantage for English majors over students of Christian studies, communications, early childhood studies, kinesiology, and sociology (all *p*'s under 0.05).

These analyses were not repeated with the Year 3 data because there were only seven English majors, too few to generalize the findings from the previous two years.

Research Question 2: Do Students' Learning Style Preferences Differ Significantly Between Declared Majors?

In order to maximize statistical power, data from all three years ($N = 1,776$) were combined before testing for significant between-group differences in students' learning style preferences. To control for Type I error and to test whether the 19 majors differed along a combination of learning style preference dimensions, a multivariate analysis of variance (MANOVA) was first conducted. Using Pillai's trace, there was a significant effect of student major on the seven learning style preference dimensions ($V = 0.21$; $F_{(126, 12,299)} = 3.04$; $p < 0.001$). Next, one-way ANOVAs were conducted for each of the seven learning styles. Significant *F* tests were followed up with post-hoc comparisons using Bonferroni correction to control for Type I error. Standardized learning style preference scores for each declared major are reported in Table 1.

Table 1

Standardized Learning Style Preference Scores by Declared Major (Years 1-3 Combined)

Declared major	<i>N</i>	Aural	Logical	Physical	Social	Solitary	Verbal	Visual
Accounting	65	0.00	0.55	-0.26	-0.31	0.07	0.11	-0.02
Business	502	-0.10	0.05	-0.03	-0.07	-0.14	-0.16	0.05
Christian studies	64	0.24	-0.08	-0.02	0.05	0.06	0.01	0.02
Communications	56	0.21	-0.01	0.19	0.31	0.24	0.00	0.09
Computer information technology	17	0.23	0.38	-0.53	-0.43	-0.09	-0.15	0.02
Criminal justice	86	-0.12	-0.01	-0.11	-0.17	-0.18	-0.02	-0.04
Early childhood	94	0.03	-0.35	0.08	0.01	0.07	-0.02	-0.26
English	35	0.01	-0.26	-0.50	-0.02	0.59	0.61	-0.27
Graphic design	15	-0.10	-0.25	-0.18	-0.13	-0.02	-0.27	1.32
Interdisciplinary	53	-0.35	-0.14	-0.03	-0.20	-0.14	-0.06	-0.14
Kinesiology	148	0.20	0.08	0.31	0.14	0.00	-0.04	0.12
Liberal studies	212	0.03	-0.19	0.01	0.04	-0.03	-0.14	0.03
Marketing	14	0.24	0.13	0.50	0.38	0.52	0.28	0.71
Organizational leadership	30	-0.02	-0.16	-0.21	-0.11	-0.20	0.13	-0.15
Political science	26	-0.09	0.69	0.46	0.20	0.09	0.25	0.52
Psychology	226	0.07	-0.05	-0.05	0.09	0.09	0.18	-0.08
Public administration	43	-0.40	0.20	0.08	-0.06	0.01	0.13	-0.20
Public relations	33	0.40	0.47	0.36	0.31	0.60	0.81	-0.07
Sociology	57	-0.03	-0.07	-0.14	0.12	0.12	0.22	-0.11

Aural learners. A one-way ANOVA revealed significant between-group differences in students' preference for aural learning activities ($F_{(18, 1,757)} = 2.28$; $p < 0.01$). Post-hoc tests were conducted using Bonferroni correction, revealing no significant contrasts. However, uncorrected *t*-tests found that aural learning activities tended to be preferred by students of Christian studies, communications, computer information technology, kinesiology, marketing, and public relations. Aural activities tended to be less preferred by interdisciplinary studies majors and public administration majors.

Logical learners. Significant between-group differences were also detected in students' preference for logical learning activities ($F_{(18, 1,750)} = 4.09; p < 0.001$). Post-hoc comparisons using Bonferroni correction found that accounting majors, computer information technology majors, political science majors, and public relations majors significantly preferred logical activities. Logical learning activities were less preferred by early childhood studies majors and English majors.

Physical learners. A one-way ANOVA revealed significant between-group differences in students' preference for physical activities ($F_{(18, 1,757)} = 3.01; p < 0.001$). Post-hoc tests using Bonferroni correction found that kinesiology majors were significantly more likely to enjoy physical learning activities than were accounting majors, business majors, and English majors. Physical learning activities were also more preferred by political science majors than by students of English.

Social learners. Significant between-group differences were detected in students' enjoyment of social learning activities ($F_{(18, 1,757)} = 1.97; p < 0.05$). However, no significant differences were detected when post-hoc tests were run using Bonferroni correction. Uncorrected *t*-tests revealed that social learning tended to be preferred by communications majors, marketing majors, and public relations majors. Accounting majors and computer information technology majors tended to be less favorable of social learning activities.

Solitary learners. A one-way ANOVA revealed significant between-major differences in students' preference for solitary learning activities ($F_{(18, 1,757)} = 2.85; p < 0.001$). Post-hoc *t*-tests with Bonferroni correction found that English majors were more likely to prefer solitary learning activities than were business majors or criminal justice majors. Public relations majors were also more likely to prefer solitary learning than were business majors or criminal justice majors. Marketing majors also tended to enjoy solitary learning activities more than other majors, but this difference was not statistically significant.

Verbal learners. Between-group differences were also detected in students' preference for verbal learning activities ($F_{(18, 1,757)} = 3.88; p < 0.001$). Post-hoc comparisons with Bonferroni correction found that English majors were more favorable of verbal learning activities than were business majors or liberal studies majors. Psychology majors were more inclined toward verbal learning than were business majors. Public relations majors preferred verbal activities more so than students of business, Christian studies, communications, criminal justice, early childhood studies, interdisciplinary studies, kinesiology, or liberal studies.

Visual learners. A one-way ANOVA revealed significant between-group differences in students' preference for visual learning activities ($F_{(18, 1,757)} = 3.37; p < 0.001$). Post-hoc comparisons with Bonferroni correction revealed that graphic design majors were more likely to favor visual learning activities than were students of every other major except for marketing and political science. While marketing and political science majors tended to enjoy visual activities more than other majors, these differences were not statistically significant.

Discussion and Conclusion

Although the sample size of English majors was relatively small for both years, these data support the conclusion that English majors have a faster on-screen reading speed than business and psychology majors. Furthermore, it is highly plausible that the mean reading speed for English majors is actually higher than that of other majors as well, such as Christian studies or kinesiology. Therefore, our first research question is answered in the affirmative. Students' average online reading speed does differ significantly between declared majors.

Our second research question was also answered in the affirmative. Accounting majors, computer information technology majors, political science majors, and public relations majors significantly preferred logical learning activities. Kinesiology majors preferred physical learning activities. English majors and public relations majors preferred both solitary learning activities and verbal learning activities. Graphic design majors were most likely to favor visual learning activities. Although not statistically significant after applying Bonferroni correction, social learning activities tended to be preferred by communications majors, marketing majors, and public relations majors, while accounting majors and computer information technology majors tended to be less favorable of social learning activities. Our results were generally consistent with prior literature which has found significant differences in student learning styles across college majors (Cano, 1999).

Implications

Findings revealed that students' online reading speeds varied widely across majors, thus the PPM reading speed estimates mandated by an approving administrative team may be grossly inaccurate. Therefore, more realistic time estimates should be considered with a specific academic major in mind. Reading speed differences were most apparent among English majors, with English majors tending to be the fastest readers. This could be problematic in that many English courses are designed for and taught to non-English majors as part of a university's general education requirement. In essence, a course designer or developer, who is a content expert in English and commonly interacts with English majors and other English academics, would expect a typical student in an introductory course to read academic literature at an unrealistically fast speed. However, non-English majors may easily fall behind, feel overwhelmed, and perhaps drop or withdraw from a section as a result of the unmanageable work requirements. Therefore, engagement time estimates for general education courses should be developed with the slowest readers in mind, regardless of the discipline.

In respect to learning style preferences, these findings generally support the practice of providing a variety of learning activities within general education courses for the maximum enjoyment of all students. Course designers may also consider offering students a choice of learning activities whereby they may accomplish the same learning objective through alternate means. However, these findings may allow designers of upper-division courses more flexibility in selecting learning activities which are generally preferred by students in their respective major. For example, it may be permissible for upper-division English courses to rely more heavily on solitary and verbal learning activities without necessarily incorporating an arbitrarily mandated quota of physical learning activities.

Limitations

We analyzed incoming student data from predominantly non-traditional students in an online degree completion program. Findings may not generalize to traditional students who are transitioning directly from high school into the university setting. Findings may also vary as a function of the university's or program's enrollment requirements. In a university where all students are required to demonstrate a high degree of language arts and general academic proficiency at enrollment, the observed differences between majors may be less acute. Another limitation was the relatively small number of English majors included in the study. Additional research should be conducted with larger sample sizes in order to further confirm these findings.

While it is theoretically possible to match students' self-reported interests with their coursework experiences, it is important to note that students who prefer the style of a particular learning activity will not

necessarily be more successful with that activity. In other words, enjoyment of an activity or class does not necessarily translate into enhanced learning outcomes. Furthermore, students' self-reported perceptions of their strengths and preferences may not be accurate, as other factors, such as cultural influences, may bias their perceptions. Future research should incorporate more objective measures of students' domain-specific abilities and related learning outcomes.

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