

Remembrance

On June 16th, 2018 family, friends, and the world of online learning scholarship lost Dr. John Benard Arbaugh, known to everyone as “Ben”. Ben was a pioneer in online learning with more than 80 publications including 17 best article or best paper awards. Many of us knew Ben for his scholarship on the Community of Inquiry model and for his work as an evaluator on national projects such as the Predictive Analytics Framework (PAR).

Ben served as Editor of *Academy of Management Learning & Education* and was a past chair of the Management Education and Development Division of the Academy of Management. He was the 2009 GMAC Management Education Research Institute Faculty Research Fellow, and was named as a University of Wisconsin Oshkosh Rosebush Professor in 2011.

Ben’s online teaching and learning research earned best article awards from the *Journal of Management Education* and the *Decision Sciences Journal of Innovative Education*, impact awards from *Business and Technical Communication Quarterly* and the *Journal of Management Education*, and several conference best paper awards.

Ben also had many scholarly publications in graduate management education and the use of bibliometrics in business and management education research. He was an Associate Editor for the *Decision Sciences Journal of Innovative Education* and served on the editorial boards of numerous journals, including the *Academy of Management Learning and Education*, the *Journal of Management Education* and the *Online Learning Journal (OLJ)*.

Ben’s instructional activities also garnered widespread recognition. In 2008 he won the UW Oshkosh College of Business Outstanding Graduate Faculty Award. He won the Outstanding Faculty Award from the UW MBA Consortium in 2012 and again in 2017. In 2013 Ben received the UW Oshkosh Edward Penson Distinguished Teaching Award.

He shared his expertise in online teaching and learning for many activities including teaching in the UW MBA Consortium, developing Shareable Content Objects as part of a UW System FIPSE grant, advising for the Kent State University *Partners Investing in Nursing’s Future Program* and with Dr. Peter Shea, served as an external evaluator for the Predictive Analytics Framework (PAR) and the UMUC predictive modeling of student success initiatives.

Ben’s passing is felt by the many colleagues and coauthors with whom he worked around the world. He was a true mentor, teacher, scholar and friend.

Peter Shea, PhD

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Introduction to the Special Issue: Best Papers Presented at the OLC 2017 Accelerate Conference on Online Learning and the Innovate 2018 Conference

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The Online Learning Consortium (formerly the Sloan Consortium, or Sloan-C,) started in the 1990s when a small community of higher education professionals came together to promote the idea that online learning could be of great benefit to providing access to a quality education. Funded by the Alfred P. Sloan Foundation, this community embarked on a number of activities designed to promote the concept that the design and implementation of online and blended learning applications needed to be well-planned and based on sound pedagogical approaches. The Online Learning Consortium (OLC) has now evolved to become the leading professional organization devoted to advancing quality online learning, to providing professional development for administrative leaders, faculty, and support service individuals and to producing high-level publications and information resources. Critical to achieving its goals, has been the development of quality conferences where individuals from around the globe share research and best practices. These conferences had their beginning in 1995 when a one-day meeting of grantees of the Alfred P. Sloan Foundation's *Anytime, Anyplace Learning* Program met in Philadelphia to discuss their work and share their experiences. Ninety individuals attended this first gathering. This meeting grew into an annual event for the next five years. In 2001, it was decided that the event be expanded into a full conference with a formal, peer-reviewed call for proposals and workshops, and would include exhibit areas. The University of Central Florida agreed to host the conference in Orlando in November. That was a fateful decision as the attack on the World Trade Center on 9/11 followed by the anthrax scare in Florida in October of that same year severely limited the number of people willing to fly to Orlando to attend the conference. Still, three hundred and sixty participants attended to share and discuss research, effective practices, student services, and administrative support for online learning. Since 2001, the conference has grown and has evolved into the "go to" event for presenting current ideas, research, and best practices in online learning.

In November 2017, the Online Learning Consortium held the 23rd International Conference on Online Learning which was renamed OLC Accelerate in 2016. Over 2,700

individuals attended this conference either in person or virtually. Seven hundred and sixty proposals were submitted for presentation, of which 461 were accepted.

In April 2018, the Online Learning Consortium held its third OLC Innovate Conference with over 1,800 in-person or virtual attendees. Four hundred and ninety-three individuals submitted presentation proposals, of which 284 were accepted.

The six articles selected for this special issue represent the best of the 623 papers accepted for presentation at these two venues, as determined by the conference track chairs and editorial staff of the *Online Learning* journal.

The Articles

The six articles in this special edition represent a wide variety of topics and issues. The findings, conclusions and commentary add significantly to our understanding of online and blended learning. These articles also represent an excellent mix of research methods and inquiry. Scholars, doctoral students and others interested in research may find important insights into methodological techniques as used by the authors of these articles.

In the lead article, “Adaptive Learning: A Stabilizing Influence Across Disciplines and Universities,” Charles Dziuban, Colm Howlin, Patsy Moskal, Connie Johnson, Liza Parker, and Maria Campbell, report on an adaptive learning partnership among The University of Central Florida, Colorado Technical University, and the adaptive learning provider, Realizeit. A thirteen-variable learning domain for students forms the basis of a component invariance study. The results show that four dimensions: knowledge acquisition, engagement activities, communication, and growth remain constant in nursing and mathematics courses across the two universities, indicating that the adaptive modality stabilizes learning organization in multiple disciplines. The authors contend that similar collaborative partnerships among universities and vendors is an important next step in the research on adaptive learning.

The second article, “Gamify Online Courses with Tools Built into Your Learning Management System (LMS) to Enhance Self-Determined and Active Learning,” by Cheng-Chia (Brian) Chen, ChingChih (Kathy) Huang, Michele Gribbins, and Karen Swan examines the growing field of gamification. The article comments that while “gamified” active learning has been shown to increase students’ academic performance, engagement, and to make more social connections than standard course settings, the costs to use educational gaming can be problematic. The first objective of the authors was to evaluate the effectiveness of gamification using existing techniques (e.g., simple HTML-based games) and readily available collaborative tools (e.g., wikis) from a typical learning management system (LMS) such as Blackboard. The second objective was to examine students’ attitudes towards gamification (e.g., usefulness). An online survey was given to 80 graduate students who took an entry-level biostatistics course from 2015 to 2017 at a Midwestern university in the United States. This study was conducted in an experimental group (class with implementation of gamification) and control group (class without implementation of gamified activities) that were randomly selected from graduate level statistics courses. A Welch’s independent *t*-test revealed a significant difference ($p < 0.001$) in the mean exam scores of experiment and control groups. A difference favored the classes with gamification. The findings suggested that using built-in LMS tools to design gamified learning activities may enhance students’ academic performance, competencies gained, and learning effectiveness, as well as provide more diversified learning methods and motivation, and offer easy modifications for different learning needs.

In “Strengths-Based Analysis of Student Success in Online Courses,” Carol S. Gering, Dani’ K. Sheppard, Barbara L. Adams, Susan L. Renes, and Allan A. Morotti provide the results of an explanatory sequential, mixed methods study that was conducted in three phases at a public research university to explore personal, circumstantial, and course variables associated with student success. The major assumption of this study was that while online learning provides broader access to higher education, the scholarly literature also reveals concerns over low retention rates in online courses. In Phase One, existing data on student enrollments across four years were analyzed at a public research university. During Phase Two, a subset of Phase One students from a single semester was invited to complete an assessment of non-cognitive attributes and personal perceptions, followed in Phase Three by interviews among a stratified sample of successful students from the previous phase to elaborate on factors impacting their success. Quantitative analyses identified seven individual variables with statistical and practical significance for online student success. Interestingly, the combination of factors classified as predictive of success changed with student academic standing. The impact of differential success factors across academic experience may explain mixed results in previous studies. The themes that emerged from the interviews with students were congruent with quantitative findings. A unique perspective was shared when students discussed “teaching themselves,” providing additional insight into perceptions of teaching presence not formerly understood. The combination of a more contextual research approach, a strengths-based perspective, and insights from student perceptions yielded important implications for educational practice.

In the next article, “Student Perceptions of the Most Effective and Engaging Online Learning Activities in a Blended Graduate Seminar,” Alicia Cundell and Emily Sheepy examine effective designs of learning activities in online environments. The major data collection activity was a questionnaire administered in three sections of a not-for-credit intensive blended graduate seminar in university teaching. The online course activities included readings, videos, discussion forum activities and other activities using a range of web-based technologies. Students rated each of the activities on four target criteria: alignment with the course learning outcomes, deep learning, engagement, and value. Students also were asked to identify the most useful activities for each of the five modules and evaluate the course as a whole in terms of navigation, expectations, instructions, availability of materials, instructor presence, and technical quality of media. The results suggested that students’ perceptions of the activities followed very similar patterns across the four target criteria. The article highlights four distinct design features that characterize the most highly-rated activities.

The fifth article in this special edition is entitled, “Effective Tagging Practices for Online Learning Environments: An Exploratory Study of Tag Approach and Accuracy,” authored by Vanessa P. Dennen, Lauren M. Bagdy, and Michelle L. Cates. This exploratory study examined a student tagging activity within a five-week social bookmarking unit. Students in six sections of a course were tasked with locating, tagging, and then highlighting and discussing course-related materials using Diigo, a social bookmarking tool. Three different tagging approaches were tested: dictionary only, freestyle only, and dictionary + freestyle. Analysis focused on accuracy and rates of student tagging, and popularity of different tag types. Findings show that most students were able to tag with high rates of accuracy after a single brief lesson. The dictionary-only approach led to fewer tags overall as well as fewer single-use tags than freestyle tagging. It also resulted in students applying useful classes of tags, such as type of content that did not emerge within the freestyle tag groups’ folksonomies. However, freestyle tagging was not without its merits, and provided opportunities for students to include tags that reflect relevant interests and more specific

topics that were not addressed in the tag dictionary. The combined approach, if carefully taught and applied, appears to have the greatest potential for supporting student information literacy skills.

Last but not least, Vicki S. Cook and Rhonda L. Gregory explore various new technologies in “Emerging Technologies: It’s Not What *You* Say – It’s What *They* Do.” The authors note that they believe that learning is not a complete circle when evaluated by what educators do, the technologies used, nor how knowledge is communicated to students. Learning is only successful when it fully assesses the impact of preparations and presentations on student outcomes. Students need the opportunity to actively participate in the *doing* of learning. The authors concluded that modeling the literacies needed to enable us to meet the needs of our future world through strong use of technologies in a heutagogical setting leads to learning success.

In closing, the editors of this special edition would like to acknowledge the efforts of a number of individuals who made critical contributions to this issue, particularly Sturdy Knight and the staff of the *Online Learning* journal (*OLJ*); Peter Shea, for his guidance as editor of *OLJ*; Kathy Ives, for her leadership and direction in navigating the Online Learning Consortium; and the OLC staff and program committees for their efforts and dedication in organizing the conferences at which the authors originally presented their research. The editors of this special issue hope our readers enjoy reading these articles and we welcome any comments.

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Adaptive Learning: A Stabilizing Influence Across Disciplines and Universities

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Abstract

This study represents an adaptive learning partnership among the University of Central Florida, Colorado Technical University, and the adaptive learning provider Realizeit. A 13-variable learning domain for students forms the basis of a component invariance study. The results show that four dimensions—knowledge acquisition, engagement activities, communication, and growth—remain constant in nursing and mathematics courses across the two universities, indicating that the adaptive modality stabilizes learning organization in multiple disciplines. The authors contend that similar collaborative partnerships among universities and vendors is an important next step in the research process.

Keywords: online courses, academic achievement, adaptive learning, blended learning, digital learning, college students, educational strategies

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Adaptive Learning: A Stabilizing Influence Across Disciplines and Universities

Gelsinger (2018) recently commented on the impact of today's technology:

It may feel like the pace of technology disruption and change these days is so dizzying that it could not possibly get any more intense. Yet here's the science fact: the pace of change right now is the absolute slowest it will be for the rest of your life. Fasten your seatbelts. It's going to be a fascinating ride. (p. 7)

This quote emphasizes the growing impact of technology in higher education, including the emergence of predictive analytics, virtual and augmented reality, online and blended courses, flipped classrooms, and a recent innovation: technology-mediated adaptive learning (Johnson, 2017; Pugliese, 2016). These instructional technologies have important implications for the

American educational system, but the potential for change in the adaptive learning process encompasses much of what has come before. Those technological developments may alter the teaching and learning process, but adaptive learning also modifies the most critical factor—*time*. Educators recognize that it takes some learners longer than others to understand a concept, develop a skill or demonstrate mastery. Students with the same motivation and ability levels require varying amounts of time to acquire knowledge. This is not only true *between* individual students but *within* individuals. Some of us might be able to acquire statistical concepts rapidly but take much longer with foreign language learning and vice versa (Thurstone, 1938; Gardner, 2011).

In 1963, John Carroll framed a model of the adaptive learning process with these statements:

Briefly, our model says that the learner will succeed in learning a given task to the extent that he spends the amount of time that he needs to learn the task.... First, spending time means actually spending time on the act of learning. “Time” is therefore not “elapsed time” but the time during which the person is oriented to the learning task and actively engaged in learning. (p. 2)

Educators understand the importance of nonequivalent learning time but have been constrained by the structure of the current educational system that most often sets a fixed learning time frame, making learning outcomes variable. But, if learning outcomes are held constant, then it follows that learning time will be the variable. Many current adaptive learning platforms that incorporate machine learning and decision-making provide a workable solution to the problem. There are other advantages embedded in these systems, including multiple learning paths, continual assessment incorporated into the instructional process, redirection to needed knowledge and skills, tailored instructional modalities, real-time instructor awareness of student status, and responsiveness to multiple learning behaviors. Most importantly for this study, these adaptive platform characteristics result in a wealth of data on the structural organization of learning, thereby enabling contextual comparisons.

The implications of this approach for teaching and learning impact every aspect of the educational process. First, adaptivity cedes much of the learning control to the student. In a truly adaptive course, students can negotiate their learning trajectory at a self-determined pace, in some cases finishing the requirements in a few days or weeks, or extending the semester past the scheduled end date. Dziuban, Howlin, Johnson, and Moskal (2017) confirm this by identifying several different successful behavior types in adaptive courses. For instance, the University of Central Florida finds a substantial cohort of students whose math placement score places them into intermediate algebra—a course that does not provide the necessary math credit but is a prerequisite to the for-credit college algebra. However, upon completing intermediate algebra in the adaptive modality, students may move to and complete college algebra in the same semester. On follow-up surveys, this led some students to ask, “Why do we need semesters?” This suggests that mathematics can be transformed into a well-planned set of contiguous skills rather than a group of courses. The same seems possible for most disciplines that have a hierarchical learning structure.

Adaptive learning alters the psychological learning contract between students and instructors—a feature of mutual understanding or misunderstanding that is vital to the learning process. The theory, originally developed by Argyris (1960), describes the implied relationship between employees and employers but has implications for the learning environment. These contracts consist of perceived obligations between students and instructors that are never expressly

stated but become organic and subjective. However, they have well-defined components: voluntary choice, agreement, incompleteness, presence of numerous contract makers, plan for managing unsuccessful contract losses, and a relational model between student and teacher (Rousseau, 1990). In higher education, Dziuban, Moskal, Kramer, and Thompson (2013) demonstrate that violation of psychological contracts involves course rhythm, expectation rules, progression, engagement, and responsiveness. Students and instructors expect different things, leading to the potential for a toxic class environment. Adaptive learning, with clearly specified expectations and continuous assessment, eliminates most aspects of violated psychological contracts in education.

Faculty importance increases in the adaptive environment because they can identify learning objectives for students through course design and analytics data provided by the system. Instructors can suggest effective interaction and intervention with students in areas that require support or additional instruction. Faculty members have a real-time view of student progress that is not available in other methods of teaching. For instance, adaptive systems can reliably identify skills or concepts with which the class on average is excelling or having difficulty. In addition, instructors can track individual student progression through course content. This provides faculty the opportunity to modify their lecture, activities, or homework assignments in order to personalize instruction.

The characteristics of adaptive learning comprise a complex learning system that exhibits properties surpassing other instructional technologies. Page (2010) summarizes the phenomenon this way:

Complex systems are collections of diverse, connected, interdependent entities whose behavior is determined by rules, which may adapt, but need not. The interactions of these entities often produce phenomena that are more than the parts. These phenomena are called *emergent*. Given this characterization, the brain would count as a complex system, so would a rainforest, and so would the city of Baltimore. Each contains diverse, connected entities that interact. (pp. 6–7)

This study seeks to understand the emergent properties of adaptive learning by identifying the latent dimensions underlying the process in courses across multiple disciplines and two structurally different universities. The objective is to determine if differing disciplines and university contexts alter learning patterns, thereby impacting effectiveness across diverse landscapes. However, this study not only involves the two universities but also the adaptive learning provider (Realizeit) in a working partnership that capitalizes on the strength of each organization. This is a study of the adaptive learning *process* and not the *platform*. In this paper, we will argue that these working partnerships, independent of marketing pressures, are essential and that those organizations that are called (we hope historically) vendors are becoming a vital part of the what Floridi (2014) terms *e-ducation*, where learning is continually delocalized, uniform, and global, and the real challenge is not what to teach but how to teach.

Background on Adaptive Learning

Adaptive learning's resurgence is due, in part, to modern computing technologies that manage large datasets and run machine learning algorithms quickly and efficiently. The concept is not new (Carroll, 1963), but more sophisticated online platforms make it increasingly viable as an instructional modality. Educators and researchers are investigating the use of this technology

in part due to an increase in performance metrics and funding that ties to the continuing need to improve student success and retention.

Adaptive learning acts like a GPS for students. As they progress through the course content, it allows for personalized instruction while altering their pathways through course objectives. It continually assesses their knowledge, helping them efficiently and effectively progress through the course (Moskal, Carter, & Johnson, 2017). This ability to allow students to either advance or remediate is one of the reasons adaptive learning is being investigated for its potential for mastery learning (Bienkowski, Feng, & Means, 2012; Dziuban, 2017). The enthusiasm is likely to continue, with several national reports pointing to adaptive learning as one of the important and influential developments in education (Becker et al., 2017; Legon & Garrett, 2018; Office of Educational Technology, 2017).

Vendor platforms vary widely in support, content, and adaptivity, as the adaptive choices continue to grow (Brown, 2015; Tyton Partners, 2016). Content-agnostic platforms provide the faculty or institution with control over the structure and logic of the system, as well as the ability to develop content from the ground up. While faculty often prefer this level of control over course content and assessment, platforms with built-in courses provide quicker and easier solutions but often are limited with respect to modification. The opportunity cost associated with expedited application is that educators have minimal ability to customize the content or assessment with these courseware options when compared to content-agnostic platforms. Many off-the-shelf courseware choices involve general education courses or other offerings that may be similar in content across many higher education institutions (Brown, 2015; Tyton Partners, 2016). In response to faculty requests for more control, platforms are providing some ability to change or modify aspects of the system. Similarly, vendors offering those adaptive platforms on the content-agnostic end of the spectrum recognize the need to help faculty who may want to expedite their course development. Vendors may provide instructional design support when their adaptive courseware has significant authoring capabilities and facilitates the importing of existing courses or open educational resources to alleviate some of the course design burden for faculty. Research indicates this workload and change in technology can increase faculty reluctance to engage in adaptive learning (Betts & Heaston, 2014). Increased support and training can help ameliorate faculty hesitation (Wingo, Ivankova, & Moss, 2017), especially when combined with release time and training for them (Kennedy, 2015). Institutional support is necessary for successful implementation of any instructional technology, including adaptive learning (Buchanan, Sainter, & Saunders, 2013; Dziuban, Moskal, & Hartman, 2016; Bastedo & Cavanagh, 2016; Pugliese, 2016; Johnson & Zone, in review).

Several national initiatives provide funding for investigating adaptive courseware's potential in higher education (Bill and Melinda Gates Foundation, 2014; Association of Public & Land-Grant Universities, 2016; Online Learning Consortium, 2016), and while some preliminary results have been positive, much more work is necessary. Varied campus climates and adaptive courseware implementations can make comparisons and generalizability of findings difficult, thereby making the research to date not nearly as prolific or promising as hoped.

Adaptive Learning's Impact on Student Learning and Attitudes

A meta-analysis conducted by SRI researchers Yarnall, Means, and Wetzel (2016) reports on findings from institutions receiving funding through the Bill & Melinda Gates Foundation Adaptive Learning Market Acceleration Program (ALMAP). The grant provides support to 14

higher education institutions to investigate the use of adaptive courseware for improved outcomes for low-income students in 15 key gateway general education and seven developmental education courses. Nine adaptive products were used in 23 courses from summer 2013 to winter 2015. This study combined the institutions' research results, including data on 19,500 students and 280 instructors. Overall, results were mixed, with researchers finding no significant impact on grades for most of the courses and with slightly higher outcomes for four out of the 15 implementation sites. In general, adaptive learning did not improve students' odds of successful course completion. The report identifies challenges impacting the research, including the variety of designs and platforms across the many institutions, making comparisons indeterminate, at best.

A case study funded by the Bill & Melinda Gates Foundation and conducted by the Boston Consulting Group and Arizona State University (Bailey et al., 2018) reports on several universities that have found gains in student success in courses utilizing adaptive learning. Georgia State University found a decrease in DFW rates for minority and Pell-eligible students in introductory writing courses. Arizona State University found positive outcomes in biology where students had a 2% increase in success (ABC grade) in adaptive mixed-modality courses compared to traditional mixed-modality courses. When controlling across assessments and faculty, investigators found even greater gains. Results in college algebra were highest in traditional, (nonadaptive), face-to-face courses, although adaptive mixed-modality showed 11% higher success rates than comparable, nonadaptive, mixed-modality courses.

Colorado Technical University achieved gains in pass rates for Trigonometry (from 76% to 94%) and a decrease in course withdrawal rates (from 36% to 17%) by incorporating adaptive learning into traditional instruction. They found similar gains in student success in Calculus with pass rates increasing from 66% to 94% and withdrawal rates decreasing from 45% to 13%. In addition, students performed better in the next math sequence course, Calculus, when adaptive learning was utilized in the prerequisite math courses (Daines, Troka, & Santiago, 2016).

The extensiveness of learning analytics data available as a student progresses through adaptive learning content allows for more granularity in identifying changes to their level of content knowledge. Researchers identified the ability to identify at-risk students early (Dziuban, Moskal, Cassisi, & Fawcett, 2016) and more precise measurement of learning that expedites mastery, improves course outcomes, and ultimately leads to increased student retention (Nakic, Granic, & Glavinic, 2015; Alli, Rajan, & Ratliff, 2016; Smith, 2013).

Students respond positively about the use of adaptive learning, finding it blends seamlessly with their online course components. As an instructional tool, personalization is found by students to be key to helping them learn the course material while increasing engagement (Dziuban, Moskal, Cassisi, & Fawcett, 2016). These findings appear to be independent of university contexts, indicating that students see the value of adaptive learning and are positive about engaging with this instructional method (Dziuban, Howlin, Johnson, & Moskal, 2017; Dziuban, Moskal, Johnson, & Evans, 2017).

Study Purpose

This study sought to identify the underlying learning dimensions (components) for students in an adaptive educational environment across different disciplines in two organizationally and structurally diverse universities that serve considerably different student populations. The findings have implications for the fields of learning science and predictive analytics by identifying the viability of constructed variables that reduce the problem of the small predictive power of

individual measures and the complexity of incorporating their interactions. This area of inquiry has a long history in many scientific areas: for example, in education by identifying the elements of learning quality (Quality Matters, 2014); in psychology's development of the Big Five personality characteristics (Tupes & Christal, 1992; Goldberg, 1992); in cultural anthropology's identification of the necessary characteristics for animal domestication (Diamond, 2005); and the standard model in quantum physics (Kibble, 2015). Although the methods for identifying fundamental components in these fields vary, the objective is the same—find a robust theory that frames better understanding. However, such an undertaking must address questions that fall into three categories before proceeding to the operational phase of development:

1. Are the components common and independent across discipline and institution?
2. Are the components disparate and contextually specific to disciplines and institutions?
3. Are there some partial patterns of communality that depend on discipline and institution?

An affirmative answer to the first question enables the possibility of an operational study. However, answering yes to questions two and three makes future development much more complicated, reducing the possibility of a common solution.

Methods

The University Partnership

Colorado Technical University

Colorado Technical University (CTU) began operation in 1965. In 2000, CTU offered online programs for the first time, and the university now offers over 50 core academic programs—from associate to doctorate—that are delivered fully online or in a blended format at the two campuses located in Colorado. Currently, the student population is approximately 25,000.

CTU's mission is to provide industry-relevant higher education to a diverse student population through innovative technology and experienced faculty, enabling the pursuit of personal and professional goals. Programs are offered in career-focused disciplines, including engineering, computer science, health sciences, business and management, criminal justice, and information technology.

CTU serves a diverse population, and the average age for online students is 36, with female students accounting for 60% of the population. CTU is an open enrollment institution, and students enter CTU with varying levels of academic and professional experience in addition to transfer credit.

Due to the diversity of the needs of a nontraditional, open enrollment student population, CTU began piloting adaptive learning in 2012. Those pilots began with implementing adaptive learning in three general education courses, including two math courses and one English course. Approximately 100 students were involved with the initial pilots in these three first-year courses, traditionally seen as courses that are barriers to student success.

The University of Central Florida

As one of the 12 public universities in Florida's state university system, the University of Central Florida (UCF) is a metropolitan research institution serving over 66,000 students with an average age of 24 (UCF, n.d.-b). Digital learning is strategically used at UCF to increase

educational access for students, and the university offered its first online course in 1996. Over 42% of student credit hours are in online and blended courses. The majority of students take a variety of course modalities, with 81% of students taking at least one online or blended course and 72% at least one fully online course in the 2016–2017 academic year. Online and blended learning accounts for the majority of UCF’s enrollment growth and the Center for Distributed Learning (CDL) provides both faculty and student support for these courses (Center for Distributed Learning Division of Digital Learning, n.d.).



In 2014, UCF began investigating the use of adaptive learning as an instructional technology for faculty to use. Its promise of personalized instruction was attractive for the potential to improve student success in key courses. After vendor demonstrations and discussions and with faculty input, Realizeit was chosen as the enterprise platform for adaptive learning. Its adaptivity and customization were important to faculty who wanted to control the content of their courses. Three faculty volunteered to participate in the pilot, and in fall 2014 the first adaptive learning courses went live with two courses: General Psychology and Pathophysiology, with 154 students enrolled in both courses (College Algebra followed in spring 2015). The use of adaptive learning in online and blended courses is supported through the university distributed learning student fee as established by Florida statute (UCF, 2012).

Creating adaptive learning courses is time-consuming. To help facilitate faculty adoption, CDL established a team of instructional designers to support personalized adaptive learning (PAL). Adaptive learning faculty are required to complete a faculty development program (PAL6000). The PAL team currently consists of four instructional designers (IDs) who are “fluent” in Realizeit and work with faculty during PAL6000 to help them understand the features of the adaptive platform system while creating pedagogically sound courses (Chen, Bastedo, Kirkley, Stull, & Tojo, 2017). The IDs are assigned to faculty for the duration of the course administration. In addition, the CDL has graphic artists, a video team, and programmers who support faculty as they design their online instructional components and teach the digital learning courses (UCF, n.d.-a.).

After numerous discussions at scientific meetings, UCF and CTU began discussing how to collaborate on joint adaptive learning research. Although the universities are very different, both utilize Realizeit as their enterprise solution for adaptive learning, and joint research across the varying institutional demographics has helped inform the research and development of adaptive learning in instruction. Table 1 illustrates the status of Realizeit adoption at both CTU and UCF.

Table 1.

*Adaptive Learning at UCF and CTU**

	 UNIVERSITY OF CENTRAL FLORIDA	 Colorado Technical University
Started with adaptive learning	Fall 2014	Fall 2012
Number of adaptive courses	22 (66 instances)	254 (3,597 instances)
Typical course length	12 weeks (summer) or 15 weeks (fall or spring)	5.5 weeks
Number of students	3,325	122,194
Number of enrollments in courses	3,842	838,363
Enrollments per student	1.2	6.9

*Data provided by Realizeit; correct as of May 16, 2018

Courses Used in the Study

Both CTU and UCF have a variety of courses offered in adaptive learning. For this paper, we attempted to make comparisons across courses of similar disciplines, namely math and nursing. Table 2 provides the description of each course provided in the university course catalogs and the number of sections and students included.

Table 2.

UCF and CTU Courses Used for Comparison

UCF course	Description	Number of sections	Number of students
Intermediate Algebra	This course is designed to reinforce and develop algebra skills, including rational expressions, radicals, linear and quadratic equations, linear inequalities, and applications.	2	332
College Algebra	This course is designed to teach students about high-degree polynomials, graphs, systems of equations, and different types of functions.	5	363
Pathophysiology	This course is designed to teach students abnormalities in physiologic functioning of the human body.	9	537
CTU course	Description	Number of sections	Number of students
Introduction to Algebra	Students learn how to use symbols for numbers, basic transformations of algebraic expressions, linear relationships of real-life quantities, and solving quadratic equations.	38	6,693
Analytic College Algebra	Students review basic algebra and continue to rational and radical expressions, functions, computation with complex numbers, and solving systems of linear equations with matrices and determinants.	26	4,486
Trends in Contemporary Nursing	This course will prepare nurses for roles that can effectively respond to all the changes and challenges facing today's health care environment; this includes completing a change management project.	30	303

The Adaptive Learning Platform

The principle underlying Realizeit is to separate curriculum from content. Students encounter a substantiality increased cognitive load in any learning environment where they must navigate a curriculum and select content. The system alleviates this issue with its Adaptive Intelligence Engine (AIE), a collection of structures, algorithms, and processes that help bridge the gap between the curriculum, content, and the learner.

Within the platform, the interaction of the learner with both the curriculum and the content generates a comprehensive stream of data that powers the algorithmic adaptivity, personalization, guidance, and feedback. The more valid the information in the models becomes, the more it improves adaptation and personalization (Vandewaetere & Clarebout, 2014).

Curriculum & Content

Traditionally, a curriculum is defined by a hierarchical structure with the individual concepts to be learned at the base of the structure. Realizeit supplements this with a second level, known as the Curriculum Prerequisite Network—an acyclic graph where the nodes represent the concepts to be learned and the edges represent the prerequisite relationships that exist between them.

Just as an instructor can teach the same concept in many ways, Realizeit allows multiple pieces of content and resources to be available for each concept in the curriculum. The design is content agnostic—it is applicable in any learning domain and can deliver learning content in multiple formats.

Adaptive Intelligence Engine

The AIE is responsible for discovering and adapting to each individual learner's changing achievement, behavior, and preferences following a loop structure described in VanLehn (2006) and du Boulay (2006). They propose that adaptive systems be built upon an outer loop that decides which task the student should do next and an inner loop that organizes steps within a task. A third loop surrounds the first two levels and is required to establish model student learning parameters. The third loop in the model is responsible for learning from the student data set. These algorithms supply information across the loops, enabling them to function effectively based on the most up-to-date data.

At the core of Realizeit, the AIE is a probabilistic model using Bayesian estimation procedures with the instructor-created curriculum prerequisite network (Howlin & Lynch, 2014). The Bayesian procedure incorporates students' initial baseline results to estimate their prior knowledge. As students progress through their adaptive courses, additional outcomes enable Realizeit to suggest alternative learning trajectories. This results in continuous updates of students' ability estimates, the knowledge they have acquired, objectives that still require mastery, and recommendations for optimal paths through the course material.

Adaptivity

Students will experience learning adaptivity and personalization customized by several different mechanisms. These include the following:

- Tailoring their start position on an objective by determining which concepts they have mastered.
- Based on their behavior, attainment, performance, and progress, dynamically altering their pathway through the curriculum, including revision and practice exercises, in real time.
- Selecting the most suitable content for them as they undertake a course module, given their learning requirement at that time.
- Selecting the most appropriate pedagogical elements within a concept or objective.
- Adapting learning paths based on rules specified by the instructors or the students themselves.

Within Realizeit, the main source of adaptivity originates from the intelligence engine discussed above; however, personalization may be customized by the instructor or the students themselves.

At almost every point in the learning process, the student has final control over learning and next steps within the system. They may alter their learning path progression (trying new concepts) and alternatively undertake review (revising/practicing previous concepts). In addition, they have access to supplemental learning material, including adding, removing, and reordering course elements within the content. However, this is not a completely open landscape for students but is structured for optimal learning while allowing for flexibility. Guidance is provided by the Realizeit system that directs students toward ability-appropriate activities to increase the potential for success.

Results

Data and metrics

From the array of metrics collected by Realizeit, a small subset of key performance aggregate indicators becomes available for review within the system and may be exported to other analysis platforms. Thirteen of these metrics became the basis of this study and are detailed in Table 3.

Table 3.

Explanation of Variables

Variable	Explanation
Knowledge State (KS)	A measure of student ability. The mean level of mastery that the students have shown on topics they have studied.
Knowledge Covered (KC)	A measure of student progress. The mean completion state of each of the course objectives.
Calculated (CA)	An institution-defined combination of several metrics, mainly KS and KC, used to assign a grade to students.
Average Score (AS)	The mean result across all learning, revision, practice, and assessment activities.
Determine Knowledge (DK)	The percentage objectives on which the student completed a Determine Knowledge operation.
Knowledge State Growth (KSG)	The extent by which a student's KS has changed from the start of the course. Can be positive, negative, or zero.
Knowledge Covered Growth (KCG)	The extent by which a student's KC has changed from the start of the course. Can be positive or zero.
Interactions (IN)	The engagement level of the instructor(s) with the student. The total number of interactions.
Messages Sent (MS)	The number of the interactions sent by the instructor that were simple messages.
Total Activities (TA)	The total number of nonassessment activities started by the student.
Total Time (TT)	The total time spent on nonassessment activities started by the student.
Number Revise (NR)	The total number of node-level activities that are classified as revision.
Number Practice (NP)	The total number of objective-level practice activities.

Principal Component Analysis

The thirteen variables describing students' cognitive outcomes and behaviors from the Realizeit platform for each of the three courses from UCF, the three courses from CTU, and combined samples for each institution are intercorrelated and subjected to the principal component procedure (Mulaik, 2009). The method approximates common factor analysis by explaining the variance and relationships (correlations) among the indices and reducing the data set to a smaller dimensionality. We chose principal components for this study because the Realizeit measures were not psychometrically derived but, rather, comprise markers of student achievement and behavior and are relatively independent of each other. Principal components analysis answers the question, "Are we able to explain the correlations we have in hand by reducing them to a smaller number of common constructed variables simplifying the observed relationships?" The procedure involves a direct eigenvalue-eigenvector decomposition of the correlation matrix within the variable space and avoids the indeterminacy of common factor models. In practice, however, principal components yield a reasonably close approximation to common factor results. Components were retained for interpretation according to the eigenvalues of the correlation matrices greater than one (Kaiser & Rice, 1974), with retained components transformed (rotated) using the Promax procedure (Hendrickson & White, 1964). Component pattern coefficients with an absolute value greater than .40 form interpretation salience.

Operationally, the study involves six separate and two combined component solutions. This analysis addresses the invariance aspect of the study—that is, whether the cognitive organization of adaptive learning is constant or whether the patterns change by institution or course context. To address this, the 28 possible pairwise comparisons of the eight component solutions were examined. For each comparison, the similarity between component and total component solutions was measured using the Tucker congruence coefficient (Chan, Ho, Leung, Chan, & Yung, 1999). Analogous to the Pearson correlation, the value of the coefficient ranges from 1 (perfect congruence) to -1 (perfect inverse relationship), with 0 indicating no linear association between the two components. The pattern matrices were first subjected to the Procrustes rotation (Schönemann, 1966), ensuring maximum alignment between components. Several subsets of the 28 possible comparisons are presented and discussed here; however, the similarity metrics for the remaining comparisons are available in Appendix A. We will start by examining if the cognitive organization of adaptive learning within institutions is constant across the courses considered in this study and then examine the cross-institutional cognitive organization. The subset of comparisons used include the following:

- Internal Institutional Comparisons—comparing component solutions across samples within an institution
 - UCF
 - CTU
- Cross-Institutional Comparisons—comparing component solution from samples across institutions
 - Entire samples
 - Course level
 - Comparison of the four algebra courses
 - Comparison of the two nursing courses

Discussion surrounding the interpretation of the Tucker congruence coefficients (Chan, Ho, Leung, Chan, & Yung, 1999) focuses on the value that one can consider indicating that two components are equivalent. A summary of the possible thresholds, along with the results from a study on the interpretation of the coefficients by experts, can be found in Lorenzo-Seva and ten Berge, (2006). Values of 0.80, 0.85, and 0.90 have been used extensively to declare components equal, with Tucker providing the following guidelines: 0.98 to 1.00 = *excellent*, 0.92 to 0.98 = *good*, 0.82 to 0.92 = *borderline*, 0.68 to 0.82 = *poor*, and below 0.68 = *terrible*. From their research on expert interpretation, Lorenzo-Seva and ten Berge (2006) recommended that values between 0.85 and 0.94 be considered *fair* and that any components with a value higher than 0.95 be considered *equal*. In our analysis, we use this stricter level of guidance.

However, the reader should be cognizant that these recommendations for interpretation are still somewhat arbitrary. They are rules of thumb that may prove helpful, but they are not absolute standards. While we have used a pattern coefficient salience of .4 as the cutoff, this could have been .3 or .5. Both sets of coefficients, because they are blind to the labels of the values and components, provide objective indicators of similarity and relevance. However, they do not supplant reflective interpretation and judgement. Those aspects of critical thinking remain, as they should, at the discretion of the authors and readers. These solutions are never completely clear-cut or free from the impact of interpretation.

Foreshadowing the Results

Because this study involves a complex course and university comparison, the study design requires eight separate component matrices, six similarity coefficient tables, and one similarity table (found in Appendix A). Therefore, a preliminary summary of the findings will help the reader navigate the data. Referring to the three questions posed in the Study Purpose section that we need to address before proceeding to the operational phase of development, we find that we can answer the first question in the affirmative: the components are common and independent across discipline and institution. With only minor variations, the same four principal components emerge within and across courses and universities. The components are clearly defined, exhibiting good approximation to simple structure. Visual inspection and the computed similarity values confirm strong correspondence among similarly named dimensions. To facilitate understanding of the four components we present a shorthand notation rubric for them. The components are fully explained in the conclusion of these results, but their notation and name are common to all tables that follow.

Knowledge Acquisition (KA) indicates a cluster of variables that indexes the degree to which students achieved mastery in the course nodes and modules. This component always appeared first and accounted for the largest proportion of variance.

Engagement Activities (EA) correlates with variables that measure to what degree students actively participate in their courses. This component always appears second because of the moderately diminished variance that can be attributed to it.

Growth (G) loads on variables that measure the change in knowledge acquisition. This component is clear but at times was either the third or fourth component to emerge.

Communication (C) is the interaction component and relates to the social learning aspect of adaptive learning. Like G, it tends to alternate between the third and fourth positions.

Internal Institutional Comparisons: UCF

The component pattern matrices for samples from the UCF courses Intermediate Algebra, College Algebra, and Pathophysiology are given in Table 4, Table 5, and Table 6, respectively. The four extracted components from the Intermediate Algebra sample pattern solution have associated eigenvalues of 4.0, 3.0, 1.8, and 1.2, and these four components capture 76.9% of the variance found in the original 13 variables. For College Algebra, the eigenvalues are 4.5, 2.1, 2.0, and 1.4, again capturing 76.9% of the variance, and for Pathophysiology, the eigenvalues are 3.8, 2.7, 1.7, and 1.1, capturing 75.1% of the variance. All three solutions have a low absolute average correlation between the components, with values of 0.27, 0.23, and 0.12 for Intermediate Algebra, College Algebra, and Pathophysiology, respectively.

Table 4

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Intermediate Algebra at UCF (n = 332)

Item	Components			
	KA	EA	G	C
Calculated	.94	.07	.09	-.03
Knowledge state	.94	.02	.05	-.12
Knowledge covered	.93	.02	.11	.07
Determine knowledge	.75	-.17	-.17	.16
Average score	.42	.08	-.10	-.13
Total activities	-.03	.90	.10	.11
Num. revised	.00	.90	-.05	-.05
Total time	-.09	.75	.18	.05
Num. practiced	.13	.71	-.32	-.06
Knowledge state growth	-.05	.04	.95	-.08
Knowledge covered growth	.04	-.06	.95	.06
Messages sent	.00	.03	-.01	.98
Interactions	.00	.03	-.01	.98

Table 5

Transformed (Promax) Pattern Matrix for the Realizeit Indices, College Algebra at UCF (n = 363)

Item	Components			
	KA	EA	C	G
Knowledge state	.95	-.12	-.04	.07
Calculated	.94	.03	-.01	.08
Knowledge covered	.91	.08	.01	.06
Average score	.67	-.09	-.12	-.33
Determine knowledge	.58	.19	.20	-.03
Total activities	.01	.95	.02	.04
Num. revised	.02	.88	.03	-.02
Num. practiced	-.02	.76	-.02	-.20
Total time	-.01	.44	-.17	.39
Interactions	-.01	-.01	.99	.00
Messages sent	-.01	-.01	.99	.00
Knowledge state growth	-.20	-.04	.00	.94
Knowledge covered growth	.20	-.11	.04	.84

Table 6

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Pathophysiology at UCF (n = 537)

Item	Components			
	KA	EA	G	C
Knowledge covered	.97	-.01	.12	.01
Calculated	.96	.05	.09	-.05
Knowledge state	.92	.08	.06	-.11
Determine knowledge	.79	-.24	-.26	.13
Total activities	-.04	.97	.00	-.02
Num. revised	-.03	.94	.02	-.06
Total time	-.04	.72	.08	.08
Knowledge covered growth	.09	.02	.94	.10
Knowledge state growth	.01	.15	.91	.02
Num. practiced	.14	.31	-.55	.14
Interactions	.01	.05	.00	.96
Messages sent	.00	.05	.00	.96
Average score	.09	.27	-.18	-.41

Preliminary examination of the pattern matrices yields some insights. First, each variable loads on a single component, simplifying the interpretation. Second, there is some slight variation in which variables load onto each of the components and the strength of that loading across the solutions, although on inspection there is some degree of consistency. This suggests that the level of variance in the component solutions should be small. Finally, in some cases, there is a swapping of position in similar components. Comparing Intermediate Algebra and College Algebra, components G and C swap positions.

As previously stated, the Tucker congruence coefficient (Chan et al., 1999) provides a means to compare both individual components and total patterns to measure the similarity of solutions derived from principal component analysis on the same set of variables from two samples. The congruence between the individual components for each solution for the UCF courses is provided in Table 7.

Table 7

Similarity Matrices at the Component Level for Three UCF Courses

		Pathophysiology				Intermediate Algebra			
		KA	EA	G	C	KA	EA	G	C
College Algebra	KA	.93	.05	.00	-.13	.98	.01	.03	-.02
	EA	.05	.86	-.23	.05	.04	.94	-.12	.03
	C	.05	-.03	.00	.95	.03	-.04	-.01	.98
	G	.07	.15	.92	.11	-.02	.06	.96	.02
Intermediate Algebra	KA	.98	.00	-.04	-.08				
	EA	-.01	.96	-.12	.03				
	G	.05	.11	.98	.04				
	C	.02	.03	.00	.96				

For the courses Intermediate Algebra and Pathophysiology, the highest level of similarity is along the main diagonal. That is, the first components from each course are most like each other, the second components are most like each other, and so on for all four dimensions. We use the term *alignment* to describe this matching of solutions. Using the Lorenzo-Seva and ten Berge (2006) guidelines, all components in each solution can be considered *equal* to their *aligned* component in the other solution. All other *similarity* values are close to zero. In other words, we can consider the two component solutions to be equal. This is confirmed by the measure of overall similarity, the total Tucker congruence coefficient, which for these two solutions is 0.97.

We see similarly high levels of similarity between the component solutions of College Algebra and Intermediate Algebra. The swapping of components C and G, which we discovered from examining the pattern matrices directly, becomes obvious. While the highest similarity values for each component in a solution are not found in the corresponding position in the other solution, we can still consider these two solutions to be *aligned*, as all components in one solution align with a single component in the other solution. The levels of similarity between the aligned components is again above the 0.94 threshold of Lorenzo-Seva and ten Berge (2006), which allows them to be considered *equal*. Calculation of the total Tucker congruence coefficient needed to take the positions of aligned components into account but yielded a high value of 0.97.

The final comparison is between College Algebra and Pathophysiology. Again, we see the swapping of the position of components, but the component solutions still align with each other. Here, three of the components fall slightly below the threshold to be considered *equal* but are still considered to be *fair*. The total Tucker congruence coefficient is 0.92. So, while not equal like the other solutions, the high similarity values can allow us to treat these two solutions as *approximately equal*.

Internal Institutional Comparisons: CTU

The component pattern matrices for samples from the CTU courses Introduction to Algebra, Analytic Algebra, and Trends in Contemporary Nursing are given in Table 8, Table 9, and Table 10, respectively. The components from the Introduction to Algebra sample pattern solution have associated eigenvalues of 3.3, 2.4, 1.7, and 1.5, capturing 68.5% of the variance. For Analytic Algebra, the eigenvalues are 3.5, 2.3, 1.6, and 1.4, capturing 67.7% of the variance, and for Trends in Contemporary Nursing, the eigenvalues are 3.5, 2.4, 1.7, and 1.2, capturing 67.7% of the variance. The percentages of variance explained by the component solutions for the CTU courses are slightly lower than that explained by the component solutions for UCF courses. All three CTU course-level solutions have a low absolute average correlation between the components' values of 0.08, 0.16, and 0.10 for Introduction to Algebra, Analytic Algebra, and Trends in Contemporary Nursing, respectively.

Preliminary examinations of these pattern matrices reveal some differences and similarities to those observed in the UCF pattern matrices. For example, for the Analytic Algebra components, each variable does not neatly load on to a single component. Knowledge Covered Growth and Num. Practiced both load on components EA and G. As with the UCF patterns, there is some variation in which variables load onto each of the components across the samples. Finally, there is no swapping of position in similar components across solutions.

The congruence between the individual components for each sample from the CTU courses is given in Table 11. For all three comparisons, the components align along the main diagonal, with values off the main diagonal in each matrix close to zero. As with the UCF components, this provides a simple mapping from a single component in one solution to a single component in another. This main diagonal also makes evident that there is no swapping of positions in the aligned components.

Table 8

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Introduction to Algebra at CTU (n = 6,993)

Item	Components			
	KA	EA	C	G
Calculated	.96	.09	-.02	-.02
Knowledge state	.89	-.17	-.03	.04
Average score	.88	-.12	-.02	.04
Knowledge covered	.75	.21	.03	-.04
Total activities	-.04	.92	-.03	.05
Num. revised	-.03	.82	-.10	.04
Total time	-.01	.73	-.01	.10
Num. practiced	.08	.51	.11	-.27
Messages sent	.05	-.10	.92	.04
Interactions	-.11	.03	.90	.00
Knowledge state growth	.15	-.01	.05	.82
Knowledge covered growth	.01	.19	.12	.73
Determine knowledge	.18	.15	.15	-.60

Table 9

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Analytic Algebra at CTU (n = 4,486)

Item	Components			
	KA	EA	C	G
Calculated	.95	.11	.01	-.07
Average score	.92	-.13	.00	.08
Knowledge state	.89	-.21	-.06	-.01
Knowledge covered	.81	.22	.07	-.08
Total activities	-.06	.93	.00	-.03
Num. revised	-.01	.81	-.02	-.09
Total time	.01	.63	-.06	.17
Interactions	-.04	.08	.90	-.01
Messages sent	.06	-.14	.88	.05
Knowledge state growth	-.10	.00	-.06	.76
Knowledge covered growth	.13	.40	.01	.69
Num. practiced	-.06	.44	.07	-.47
Determine knowledge	.10	.06	-.22	-.44

Table 10

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Trends in Contemporary Nursing at CTU (n = 303)

Item	Components			
	KA	EA	C	G
Knowledge state	.95	.02	.05	-.07
Average score	.89	-.12	-.02	-.04
Calculated	.88	.16	.02	.13
Total activities	-.02	.94	.05	.04
Num. revised	.12	.83	-.05	-.02
Total time	-.05	.75	.04	-.15
Num. practiced	-.14	.41	.35	.41
Interactions	.00	.00	.96	-.12
Messages sent	.05	.01	.94	-.08
Determine knowledge	-.08	.16	-.28	.65
Knowledge covered growth	-.18	.33	-.08	-.65
Knowledge state growth	.13	.36	-.12	-.53
Knowledge covered	.29	.13	-.08	.42

The highest level of similarity is between Introduction to Algebra and Analytic Algebra, with all aligned components being considered *equal* using the Lorenzo-Seva and ten Berge (2006) guidelines and with a total Tucker congruence coefficient of 0.97. Each of the other comparisons of component solutions have high levels of similarity. Analytic Algebra and Trends in Contemporary Nursing have two similarity values marginally below the threshold to be considered *equal*, whereas the Introduction to Algebra and Trends in Contemporary Nursing comparison has three similarity values marginally below the threshold. Both comparisons have a total Tucker congruence coefficient of 0.93.

Table 11

The Similarity Matrices at the Component Level for Three CTU Courses

		Trends in ... Nursing				Introduction to Algebra			
		KA	EA	C	G	KA	EA	C	G
Analytic Algebra	KA	.92	.04	-.02	-.17	.98	-.02	.00	.00
	EA	-.10	.95	.03	-.01	-.02	.99	-.03	.12
	C	.01	-.03	.96	.14	-.04	-.04	.95	.06
	G	.02	.12	-.08	.92	-.03	-.10	.03	.97
Introduction to Algebra	KA	.93	.07	-.05	-.19				
	EA	-.08	.96	.03	-.11				
	C	-.03	.01	.91	.08				
	G	.05	.23	-.02	.91				

As with the UCF course solutions, all CTU course solutions can, given such high levels of similarity, be considered *equal* or approximately so. We have shown that the cognitive organization of adaptive learning within an institution is constant across these courses. Now, our attention turns to cross-institutional comparisons.

Cross-Institutional Comparisons—Entire Samples

We begin the cross-institutional comparisons with the entire sample from each institution. Given the high level of internal similarity of solutions for each institution, one can expect the solution for each entire sample to capture the course-level solutions quite well. This can be verified by examination of the component-level Tucker congruence coefficients. This detail of analysis is not provided here, but the similarity matrices comparing the entire samples to individual courses are provided in Appendix A for the reader to verify, if desired.

The component pattern matrices for the entire sample from UCF and CTU are given in Table 12 and Table 13, respectively. The four extracted components in the UCF entire sample pattern solution have associated eigenvalues of 4.1, 2.3, 1.9, and 1.5, meaning they capture 75.4% of the variance in the original 13 variables. The components have an absolute average correlation of 0.21. The CTU components have associated eigenvalues of 3.4, 2.6, 1.6, and 1.4 and capture 69.2% of the variance. These four components have an absolute average correlation of 0.10.

Table 12

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Entire Sample at UCF (n = 1,528)

Item	Components			
	KA	EA	C	G
Calculated	.95	.04	-.01	.12
Knowledge covered	.95	.02	.02	.13
Knowledge state	.91	.01	-.10	.02
Determine knowledge	.79	-.06	.12	-.21
Average score	.37	.02	-.20	-.15
Total activities	-.05	.97	-.02	-.09
Num. revised	-.02	.90	-.15	.00
Num. practiced	.11	.61	.16	-.25
Interactions	-.01	-.02	.98	.01
Messages sent	-.01	-.02	.98	.01
Knowledge covered growth	.05	-.11	.04	.93
Knowledge state growth	-.06	-.05	-.09	.92
Total time	-.04	.30	.24	.44

Table 13

Transformed (Promax) Pattern Matrix for the Realizeit Indices, Entire Sample at CTU (n = 11,782)

Item	Components			
	KA	EA	C	G
Calculated	.96	.09	-.01	-.04
Average score	.90	-.13	-.01	.06
Knowledge state	.89	-.18	-.03	.02
Knowledge covered	.79	.20	.03	-.06
Total activities	-.04	.92	.02	.03
Num. revised	-.01	.81	-.10	-.01
Total time	-.01	.69	.03	.12
Num. practiced	.03	.47	.07	-.40
Messages sent	.05	-.10	.92	.02
Interactions	-.07	.05	.90	-.02
Knowledge state growth	.04	-.01	.03	.79
Knowledge covered growth	.08	.27	.06	.71
Determine knowledge	.14	.13	.08	-.56

The measures of congruence or similarity between the individual components for the entire sample from each institution are given in Table 14. As with some previous comparisons, the alignment is along the main diagonal. Using the Lorenzo-Seva and ten Berge (2006) guidelines, the first, second, and fourth components can be considered to have a *fair* level of congruence, while the third components can be considered *equal*. All other components' congruence coefficients are close to zero and show no similarity. The total Tucker congruence coefficient between these samples is 0.91 (see Table 15).

Table 14

The Tucker Congruence Coefficient Between Individual Components for the Entire Sample From Each Institution

		UCF entire sample			
		KA	EA	C	G
CTU entire sample	KA	.89	.01	-.10	.07
	EA	.05	.90	.06	.17
	C	.02	-.04	.97	.04
	G	-.24	-.14	-.09	.89

The source of the slightly lower levels of similarity between the KA, C, and G components can be found by examining the pattern matrices in Table 12 and Table 13. Not all variables load onto the same components or with the same weight. For example, the variable Average Score loads on the first component in the solution from the CTU sample but not in the pattern from UCF sample. Despite these differences, there is a remarkable level of agreement on the component solutions across the two very different institutions. The similarity metrics are *equal* or marginally below equal, allowing us to consider the solution underlying these two very different institutions to be *approximately equal*. This, along with our previous findings, is evidence that the cognitive organization of adaptive learning is independent of the institution, setting, or context.

The focus of the final comparison section is to take this cross institutional analysis down to the course level and confirm the findings at the institution level. To accomplish this, we pair off similar courses across the institutions. We begin by comparing the two UCF algebra courses with the two algebra courses from CTU, before moving on to the nursing courses from each institution. Cross-institutional comparisons outside of these are not described here. However, their similarity matrices are available in Appendix A.

Table 15

The Total Tucker Congruence Coefficient for Cross-Institutional Comparisons

		CTU			
		Trends in... Nursing	Analytic Algebra	Intro. to Algebra	Entire Sample
UCF	Pathophysiology	.80	.87	.89	.89
	College Algebra	.82	.91	.93	.93
	Inter. Algebra	.82	.91	.93	.92
	Entire Sample	.81	.89	.91	.91

Cross-Institutional Comparisons—Individual Course Level

The pattern matrices for each of the algebra courses have been provided in previous sections, with the solutions behind the courses within each institution showing a high level of similarity. While there is an order to each institution's courses (CTU's Introduction to Algebra precedes Analytics Algebra, and UCF's Intermediate Algebra precedes College Algebra), there is no definitive matching of the courses across the institutions, so all four possible comparisons are made. Table 16 displays the matrices containing the component-level similarities for each of the four possible comparisons.

Beginning with UCF's Intermediate Algebra and in each of the CTU algebra courses, we again see the swapping of Components 3 and 4. All similarity metrics are above the threshold to be considered *fair*, with three being above the higher threshold to be considered *equal*. The total Tucker congruence coefficients for UCF's Intermediate Algebra compared with CTU's Analytics Algebra and CTU's Introduction to Algebra are 0.91 and 0.93, respectively (see Table 15).

The similarity between UCF's College Algebra and each of the CTU algebra courses is generally high, above the *fair* threshold, with two exceptions. Both exceptions occur on the fourth component in each comparison. These similarity values are just on the border of being *fair*. The total Tucker congruence coefficients for UCF's College Algebra compared with CTU's Analytics Algebra and CTU's Introduction to Algebra are again 0.91 and 0.93 respectively, see Table 15. Despite the two slightly lower component-level values, the remaining high-level coefficients along with the high total similarity values again allow us to consider the pattern solutions as *approximately equal*.

Table 16

The Tucker Congruence Coefficient Between Individual Components for the Algebra Courses in Each Institution

	UCF-Intermediate Algebra				UCF-College Algebra				
	KA	EA	G	C	KA	EA	C	G	
CTU-Analytic Algebra	KA	.89	.02	.06	-.06	.95	-.07	-.04	-.04
	EA	.03	.90	.20	.04	.05	.90	-.04	.26
	C	-.05	.04	-.03	.94	-.05	-.02	.94	-.04
	G	-.23	-.12	.92	-.01	-.16	-.30	-.03	.84
CTU-Introduction to Algebra	KA	.90	.04	.09	-.10	.94	-.03	-.07	.01
	EA	.06	.94	.09	.04	.06	.94	-.04	.18
	C	.04	-.01	.05	.97	.02	-.02	.98	.07
	G	-.21	.03	.92	-.04	-.15	-.16	-.04	.83

The final comparison examines the nursing courses in each institution. The component-level similarity values are given in Table 17. Here we see something different occurring than in the other comparisons. Only two components have high enough similarity to be considered *fair* using the guidelines. The other two have similarity coefficients that fall below the threshold, with the similarity of the first components in each solution falling far below the threshold. The total

Tucker congruence coefficient for the comparison of these two pattern solutions is 0.80 (see Table 15), again below the threshold to be considered fair.

Table 17

The Tucker Congruence Coefficient Between Individual Components for the Nursing Courses in Each Institution

		UCF-Pathophysiology			
		KA	EA	G	C
CTU-Trends in ... Nursing	KA	.66	.16	.02	-.22
	EA	.14	.90	.21	.07
	C	-.07	.12	-.14	.89
	G	-.43	.12	.79	.06

In fact, we can observe that the total Tucker congruence coefficients are low for all comparisons involving the CTU nursing course and any of the UCF courses. There is something different about the solution of CTU's Trends in Contemporary Nursing course, which means we cannot treat its solution as equal, as we have done with all other patterns comparisons. This is likely because this course is not delivered fully through the adaptive platform. Two of the five weeks, including assessment, are delivered through traditional means. The fact that the KA and G components have low similarity values make sense considering this. While there is a difference in the solutions, there is still a high level of agreement between this course and the other courses, and the interpretation of this nursing course will not differ dramatically from that of the other courses.

Interpretation of Components

The preceding pattern matrices and similarity coefficients provide an indication that the underlying dimensions of adaptive learning remain stable within disciplines, across disciplines, and across the two universities. Although there is not complete correspondence across courses at UCF and CTU, the component similarity and invariance found in this study can be considered stable. The algebra courses align quite well; however, the nursing comparison is, at best, an approximation because comparing Pathophysiology with Trends in Contemporary Nursing reflects only a mild curricular relationship. There will always be some random variation in the results causing some variables to be unstable, drift in and out of components, and at times change their sign. This, along with our previous caveat on using the similarity interpretation guidelines as absolute standards, indicates that the findings have remained constant enough for us to make the following assertion: Based on the Realizeit indices, there are four components that comprise the adaptive learning educational environment.

Knowledge Acquisition (KA): This is the dominant component in every solution and showed consistent correspondence across all patterns. Although each variable did not appear in every KA component, it involved the following measures: calculated, knowledge state, knowledge covered, determine knowledge, and average score. These measures relate to educational achievement and have a mastery element associated with them. Knowledge acquisition in adaptive learning assesses learning prior to, during, and upon completion of a course and forms the benchmark for student success. In addition, it serves as the basis of the decision engine's recommendation about the appropriate learning path for students and an early indication of possible difficulties in the learning sequence. This component forms the basis of effective course

design and pedagogy. Knowledge acquisition appears first, is the strongest, and is the learning engine that makes cognitive growth possible.

Engagement Activities (EA): This component, appearing in every solution, bears a strong relationship to what Carroll called the time students spent in actual learning and relates to how much energy a student expends in the learning process. If one could hold ability level constant, a reasonable assumption might be that students who are more engaged in learning activities (albeit effective ones, not just marking time) will score higher on knowledge acquisition. This component is formed by relationships among total activities, number revised, total time, and number practiced, again, with not every variable appearing in every pattern. This dimension asks the following questions: How much did you do, how much did you revise, how much did you practice, and how much time did you spend in the course? There is an adage that 100% of people who do not buy lottery tickets do not win. That analogy seems to hold for adaptive learning. As a student, you may succeed with minimal engagement, but the chances of success are much greater in the adaptive modality if you do many activities, practice, and do some thoughtful revision.

Growth (G): At this point, the components become slightly more unstable. Growth is a clear expectation for any course. Measuring change in knowledge acquisition can result from many baseline measures and is a vital element of the learning cycle. In most cases, this component is formed by knowledge state growth and knowledge covered growth, with appearances in various places by number practiced, determine knowledge covered, and total time. Clearly, however, growth is change in what information a student has mastered and is the key bellwether for student progress in their adaptive learning courses. So far then, we have established the importance of the following: How much knowledge did you acquire, how much did you really engage, and how much did you grow? Although more variable, this dimension appeared in every pattern we derived.

Communication (C): Finally, communication emerges in the Realizeit platform, enabled by messages sent and interactions. Within the constraints of this modality, this is the social learning dimension of adaptive learning and the way students communicate with each other and their instructors—it indexes the interaction patterns found in adaptive learning. This dimension underlies the effort students expend communicating with each other, their instructors, and how their instructors communicate with them. Although this component is relatively independent of EA on a correlation index, it bears a strong conceptual relationship.

Additional Remarks About Complexity

Before concluding, it is worth pointing out several other interesting findings. These are highlighted by Table 18, which displays a count of the number of times each variable loaded on a component.

Table 18

Number of Times Each Variable Loaded on Each Component

Variable	Component			
	KA	EA	C	G
Calculated	8			
Knowledge state	8			
Average score	6		1	
Knowledge covered	7			1
Determine knowledge	4			4
Number practiced		7		4
Total time		7		1
Number revised		8		
Total activities		8		
Interactions			8	
Messages sent			8	
Knowledge state growth				8
Knowledge covered				8
Growth		1		8

First, we see the general pattern in each of the components emerging. This makes sense and reaffirms the high level of similarity across the various solutions. Second, notice that the determine knowledge variable loads as often on the Knowledge component as on the growth components. Examining the pattern matrices, we can see that this split is by institution. In UCF the determine knowledge variable always loads on the knowledge component, and in CTU it always loads on growth. Determine knowledge acts as a pretest on each milestone within a course and measures a student's level of prior knowledge of the concepts within that milestone. The variable measures the percentage of milestones on which the student used the determine knowledge functionality. This difference could be due to the fact that the determine knowledge functionality is being used differently in each institution. In CTU it is almost mandatory, and its use is highly encouraged by the instructors. In UCF it is an optional feature that the student can choose to use if they wish.

We see a similar loading on multiple components with the number practiced variable, which measures the number of times a student practices answering questions on concepts they have already completed. However, in this case, we do not see an even split, with the variable sometimes loading on both the effort and growth and sometimes loading on one of these components. Here the split is not by institution, as with determine knowledge, nor is it by subject domain. Again, this may suggest that this functionality is being used differently in some of these courses. It is interesting that this does not happen for the variable that counts the number of revisions. In the system, a revision includes both learning content and questions and is a targeted action on a single concept. The motivation for using the revision functionality, generally remediation, is likely different from the motivation for using practice, improvement of grade, and reinforcement of knowledge.

Limitations

There are limitations inherent in this research because the scope and generalizability are constrained. First, the study involves only two universities (UCF and CTU), one adaptive learning platform (Realizeit), and two subject areas (algebra and nursing). Although the investigators have high confidence in the validity of their findings, at best this should be considered a pilot study that may or may not generalize to all universities, disciplines, or adaptive learning platforms. Replication and expansion will add legitimacy to these findings.

Secondly, the dependent measures used to develop the component patterns are internally generated metrics provided by Realizeit. Although they prove very useful for documenting and understanding student outcomes, modeling learning behaviors, and accurately predicting which students are likely to be successful, the external validity of this research line can be strengthened. Specifically, this can be accomplished by adding achievement, behavior, and engagement variables generated outside Realizeit. This would allow for an integrated domain study where what has been accomplished in this paper might be augmented by interbattery component analysis that would anchor the Realizeit data to external validation metrics.

Thirdly, the course comparisons are formulated at the most general level. Introductory and Intermediate Algebra have not been corroborated by topic, nor have the algebra courses. In the nursing domain, Pathophysiology is highly technical and skills based, while Trends in Contemporary Nursing has more general outcome expectations.

Finally, the practical implications of the results for this study have yet to be demonstrated. Principal components are latent, nonobservable variables. We argue here that because those dimensions have remained constant and stable over such a variety of contexts, they are important. However, this study has taken place in the realm of abstraction. As a result, causal inferences, if they exist, are not identified in this study. A logical next step would be to compute and analyze the component scores for each solution within and across courses and universities.

Discussion

The Positives

Time. Adaptive learning creates a fluid educational environment responding to the needs of many student cohorts. Features like initial student knowledge baselines, continuous assessment and feedback, redesigned learning paths, mastery certification, and instructional format preference make a more flexible and responsive educational landscape. In the introduction we mention adaptive learning's modification of learning time. Adam (2004), in her work with temporal culture, provides insights into what can happen with constant outcomes and variable learning time.

Learning transforms the following aspects of a student's experience:

1. Time frame: The time boundaries of a course or program of study
2. Timing: When learning occurs
3. Tempo: The pace of learning
4. Duration: How long learning activities last
5. Sequence: The order in which learning will take place

Norberg, Dziuban, and Moskal (2011) incorporate these elements in their time-based model of blended (or adaptive) learning, grouping the educational process into synchronous and asynchronous modalities

Poverty. Adaptive learning addresses a problem in our society that, unfortunately, originates with our educational system. The expected college graduation rate for American youths living in the lowest economic quartile is approximately 9%, while that projection for the top quartile is 77% (Cahalan & Perna, 2015). If you grow up in poverty in this country, the odds against your getting a degree are nine to one. Economists place the increase in lifetime earnings from a bachelor's degree at approximately one million dollars—enough to raise someone from poverty into the middle class (Carnevale, Rose, & Cheah, 2013). Staggering college debt complicates the problem. Estimates place the current average indebtedness for college graduates at \$37,000—an amount that disproportionately impacts students living in poverty (Fay, 2018; Lochner & Monge-Naranjo, 2015). The problem is complex, but the answer is clear. Increase educational success and communities will transform themselves. However, this demands excellent education early, high expectations, continual support, and assurance that when students have an opportunity to attend vocational school, community college, or a university, the money will be available (Weiss, 2017). The cost is considerable, but the return on investment to our society will be immense (Lochner, 2010). We cannot afford not to educate our young people.

Why do students from poor neighborhoods struggle with education? Mullainathan and Shafir (2013) argue that they live in scarcity—having many more needs than resources to meet them. Students have to work at jobs with irregular hours that make time management difficult. Health care and family responsibilities place additional pressures on them. They borrow money to attend college because the complexities of applying for scholarships are overwhelming.

What does this have to do with higher education and adaptive learning? Consider what happens when an overwhelmed student misses class. The next one becomes difficult or impossible because it depends on understanding content from the previous session. Miss another one, and perhaps dropping out becomes the only option. Each class building on the previous one is not an optimal situation for students who are overloaded by scarcity.

In contrast, consider an adaptive learning course with modules supported by learning nodes and a go-at-your-own-pace design. The system can place a student at the optimal starting point corresponding to her estimated competency level. At its full potential, when running properly and with faculty support, adaptive learning can help address the scarcity problem. By empowering students to manage their learning using adaptive learning systems that identify the goal, locate where they should start, and present them with options about how they can get there, we empower instead of impede them.

A new learning taxonomy. The positives of adaptive learning coalesce around a facilitated yet rigorous educational environment. Scheduling becomes easier, giving students more control over their life circumstances. Class size is not an issue because education becomes a one-to-one experience, and the inherent design of adaptive learning requires clearly specified course requirements. Progress assessment becomes more authentic and continuous. Therefore, students see an increased likelihood of obtaining a degree and become more engaged and committed to persisting. They become active participants in their own evaluation because response time is faster. Discussing information communication technologies, Floridi (2013, 2014) coincidentally developed a learning taxonomy for adaptive learning:

Information:	Things a student knows
Insipience:	Knowledge a student lacks
Uncertainty:	Things a student is not quite sure he or she knows
Ignorance:	Things a student does not know he or she does not know

This taxonomy is the design specification for adaptive learning because, metaphorically, students and instructors have much more skin in the game, so there is symmetry in the responsibility for learning (Taleb, 2018).

The Issues

All new instructional technologies have issues, and adaptive learning's challenges include some associated with the platforms and others with education in our society. Unfortunately, we overestimate short-term results and underestimate long-term outcomes. The mixed results reported in the background section of this article can lead us to fall into that trap. The impact of adaptive learning will be realized over the long haul—years or possibly decades. Without this mindset we will jettison this pedagogy like we have done with so many others. Do adaptive learning platforms work flawlessly? No, they do not and probably never will, but they are getting much better. Just like students, they need time.

Ambivalence. Unfortunately, there is a growing ambivalence in our society about the value of an education—both intellectually and financially. Students are increasingly disenchanted with their life benefits after obtaining a degree. Consider this quote from the *Wizard of Oz*:

Back where I come from, we have universities, seats of great learning, where men go to become great thinkers. And when they come out, they think deep thoughts and with no more brains than you have. But they have one thing you haven't got: a diploma. (Baum, as cited in Caplan, 2018, p. 1)

Idealized cognitive models and boundary objects. Contemporary education and adaptive learning have two confounding issues. The first is an idealized cognitive model (ICM) (Lakoff, 2008). An ICM is a frame arbitrarily constructed because we need to make sense of our world. A good example relates to time: for instance, the notion of a month. There is no month in nature. We invented it because we needed some way of dealing with the passage of time. A month exists in the context of a year—another ICM. These are completely arbitrary, and it doesn't take much research to discover that cultures all over the world mark the passage of time differently. Adaptive learning is an ICM and is the reason we experience such difficulty forming precise definition. As an ICM it is useful but not precise as a treatment effect.

The adaptive ICM issue is confounded by Bowker and Star's (2000) theory of a boundary object. Adaptive learning is a good example. A boundary object is robust enough to hold a community of practice together but relatively weak in that community. However, individual constituencies have a very strong definition. For instance, each platform provider has a clear specification of adaptive learning that guides their system development, but they don't necessarily agree with each other. The same is true across universities. Critical thinking is another example of a boundary object. Most university communities are in favor of it, but specific disciplines disagree on its definition and composition. Adaptive learning is both an ICM and boundary object, making definition and evaluation a challenge. Both are important and necessary but increase complexity. The research objective is to move from data to information to insight to action. However, because adaptive learning is an idealized cognitive model and boundary object, we must function under the influence of uncertain mediation (Setenyi, 1995) where data are imprecise, ambiguous and at times contradictory.

Conclusion

Adaptive learning remains stable across diverse disciplines in two universities with different organizational structures and student populations. UCF is one of the largest public universities in the country, and CTU is one of the most successful for-profit institutions in higher education. Both campuses use adaptive learning to serve the needs of their student cohorts—UCF accommodates scale and diversity while CTU responds to working adults who comprise a large percentage of its student population.

The analysis is objective because the principal components analysis does not integrate the variable labels we describe; therefore, it discounts confirmation bias. The method reproduces the largest proportion of the correlation matrix with the smallest number of dimensions, thereby reducing a complex system of pairwise relationships into a simplified explanatory model. The components are clear and unambiguous involving achievement, growth engagement, and communication. Learning science suggests that there is a clear relationship between these traits—engagement and communication are prerequisites for growth and achievement. However, in this study they are statistically independent of each other. The irony is that the four constructs are no surprise, because educators know that this underlying pattern is fundamental to effective teaching and learning in all modalities, not just adaptive ones.

Because of its responsiveness, adaptive learning enables universities to accommodate demographically diverse student cohorts, potentially leveling the educational playing field. This modality acknowledges the increasingly important student voice. Learners want reduced uncertainty about how to proceed in a course without disruption from work and family demands. They want an improved sense of control and a method to monitor progress with responsive and authentic assessment. Understanding the rules and having clear course expectations at the outset are prerequisite for their engagement. Students expect a more responsive education giving them more learning latitude that increases their agency and executive control. All course modalities can accommodate the four components, but adaptive learning seems particularly well suited to them, and as the platforms improve, we conclude that students will become a more active part of teaching and learning. *Presence* is taking on whole new meaning.

This study is a collaboration between two universities and their common adaptive learning platform provider. Each organization brings different strengths to the partnership. CTU achieves scale with adaptive implementation. UCF integrates research and data into the decision-making and policy process. Realizeit brings advanced analysis skills and makes transparent analytic data available to all its partners. Because of this small network, each organization improves its adaptive learning process—the universities with pedagogy and Realizeit with its platform. This happens in a nonlinear process that encounters a good deal of productive failure. The technology does not drive the work, but rather the research helps improve the technology. The partners commit to pushing information and flexibility out as far as possible and believe that progress happens in small steps. Simple is more effective. Without the partnership and the sharing, there would be no study. None of us could do this alone. Therefore, our major conclusion is that we need more extensive collaborative work. Each university can contextualize adaptive learning, and every platform provider can support an active research agenda to form an increasingly productive, collaborative partnerships.

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Appendix A
Similarity Matrices for Each Comparison of Samples

Entire Samples vs Courses – Both Institutions	CTU - Trends in Contemporary Nursing					CTU - Introduction to Algebra				CTU - Analytic Algebra				
		KA	EA	C	G	KA	EA	C	G	KA	EA	C	G	
	CTU - Entire Sample	KA	.93	.07	-.03	-.18	1.00	-.01	-.01	.01	.99	-.01	-.02	-.02
		EA	-.09	.96	.03	-.07	-.02	1.00	-.02	.05	-.03	.99	-.03	-.06
		C	-.01	.02	.93	.09	-.02	-.02	1.00	.02	.00	-.01	.96	.03
		G	.04	.17	-.07	.92	-.01	-.04	.00	.99	-.01	.07	.03	.99
	UCF - Entire Sample	KA	.73	.11	-.08	-.44	.89	.06	.04	-.22	.87	.04	-.07	-.23
		EA	.03	.86	.10	-.16	.02	.91	-.06	-.07	-.01	.88	-.01	-.24
		C	-.13	.06	.92	.02	-.11	.05	.97	-.06	-.09	.04	.93	-.05
		G	.01	.34	-.09	.74	.07	.13	.06	.89	.05	.22	-.01	.90
	UCF - Pathophysiology					UCF - Intermediate Algebra				UCF - College Algebra				
		KA	EA	G	C	KA	EA	G	C	KA	EA	C	G	
	CTU - Entire Sample	KA	.83	.10	.05	-.19	.90	.04	.08	-.08	.95	-.04	-.05	-.01
		EA	.07	.89	.03	.05	.04	.92	.13	.05	.05	.93	-.03	.21
C		.03	.02	.01	.96	.02	.02	.02	.98	.01	.00	.98	.04	
G		-.22	.13	.93	-.03	-.23	-.04	.92	-.05	-.15	-.23	-.06	.83	
UCF - Entire Sample	KA	.99	-.02	-.03	-.07	1.00	-.01	.00	-.01	.97	.04	.02	.00	
	EA	.01	.91	-.19	-.02	.02	.95	-.11	-.01	.02	.97	-.04	-.06	
	C	.01	.02	-.05	.98	-.03	.06	-.04	.97	-.06	.05	.94	.03	
	G	.05	.14	.94	.08	-.02	.04	.97	.01	.01	-.10	-.02	.97	
CTU Courses vs UCF Courses – Nursing vs Algebra	CTU - Analytic Algebra					CTU - Introduction to Algebra								
		KA	EA	C	G	KA	EA	C	G					
	UCF - Pathophysiology	KA	.81	.06	-.05	-.22	.83	.08	.06	-.20				
		EA	.08	.87	.04	.06	.10	.89	-.02	.18				
		G	.04	.10	-.01	.94	.05	-.01	.03	.92				
		C	-.18	.05	.91	-.01	-.20	.04	.96	.00				
	UCF - Intermediate Algebra					UCF - College Algebra								
		KA	EA	G	C	KA	EA	C	G					
	CTU - Trends in Contemporary Nursing	KA	.76	.05	.03	-.10	.82	-.07	-.05	-.07				
		EA	.10	.90	.32	.05	.10	.88	-.01	.40				
		C	-.07	.16	-.13	.89	-.08	.10	.88	-.11				
		G	-.43	-.05	.75	.04	-.33	-.27	.04	.68				

Gamify Online Courses With Tools Built Into Your Learning Management System (LMS) to Enhance Self-Determined and Active Learning

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Abstract

“Gamified” active learning has been shown to increase students’ academic performance and engagement and help them make more social connections than standard course settings. However, the costs to use an educational game design with efficient delivery of the game/course plan can be problematic. Our first objective was to evaluate the effectiveness of gamification by using existing techniques (e.g., simple HTML-based games) and readily available collaborative tools (e.g., wikis) from a typical learning management system (LMS), such as Blackboard. Our second objective was to examine students’ attitudes toward gamification (e.g., perceived usefulness). An online survey was given to 80 graduate students who took an entry-level biostatistics course from 2015 to 2017 at a midwestern university in the United States. Our study was conducted using an experimental group (class with implementation of gamification) and control group (class without implementation of gamified activities) that were randomly selected from graduate-level statistics courses. A Welch’s independent *t*-test revealed a significant difference ($p < .001$) in the mean exam scores of the experimental and control groups. The difference favored classes with gamification. The findings suggest that using built-in LMS tools to design gamified learning activities can enhance students’ academic performance and the competencies gained, as well as provide more diversified learning methods and motivation, and offer easy modifications for different learning needs.

Keywords: gamification, game-based learning, online learning, LMS, engagement

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Gamify Online Courses With Tools Built Into Your Learning Management System (LMS) to Enhance Self-Determined and Active Learning

Gamification and game-based learning have been the buzzwords in a variety of disciplines, including education, math, statistics, business, computer science, and health-related professions (Dicheva et al., 2015; Hamari, Koivisto, & Sarsa, 2014; Seaborn & Fels, 2015). The definition of “gamification” has been quite challenging to pin down because of multiple applications in a variety of formats. Thus, it might be easier to understand the

definition of “game” first before educators arrive at definition of gamification. According to game/gamification theory literature, *game* can be defined as “a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome” (Salen & Zimmerman, 2004, pp. 80–81). A standard definition of *gamification* was proposed by Seaborn and Fels (2015) that “gamification is the intentional use of game elements for a gameful experience of non-game tasks and contexts” (p. 17). In practice, gamification in education has been used with gamified designs in an instructional system that supports nongame activities to increase student engagement and learning motivation in a fun atmosphere.

The prominence of the digital game medium in popular culture and personal entertainment has increased interest in the study of the effectiveness of gamification in enhancing academic performance and educational relevance in the digital age (Seaborn et al., 2015). More frequent and comprehensive implementation of gamification and gamified activities has been increasingly recognized in business and education (Hamari et al., 2014; Seaborn et al., 2015; Yildirim, 2017). The concept of gamified learning extends educators’ application of traditional teaching strategies and provides an attractive method that may facilitate students’ engagement and increase their academic performance.

The applications of gamification for online courses have been limited. Gamified active learning could increase student engagement, create enthusiasm, provide instant feedback, and make more social connections than standard online course settings (Seaborn et al., 2015). However, the costs to use an educational game design with effective delivery of the game plans and course contents can be problematic, especially for instructors without extensive knowledge in computerized gaming and/or a budget to create such environments (Kapp, 2012). Moreover, it can be difficult to find a good fit between the games on the market and course learning objectives. In addition, instructors may have insufficient resources and training in online teaching technology to even initiate game settings in online courses.

To take advantage of the possible benefits from gamification and overcome the above challenges in online learning environments, there is a strong need to develop innovative gamified activities based on the capabilities of the existing techniques (e.g., simple HTML-based games) and readily available collaborative tools (e.g., wikis) from the most commonly used learning management systems (LMS), such as Blackboard, Canvas, Moodle, or D2L. To contribute to the present knowledge of gamification in online learning and higher education, our research aims were (1) to investigate whether gamified activities for online graduate-level statistics courses can improve students’ academic performance and perceived statistical competency, (2) to explore whether the implementation of gamification can enhance online students’ engagement, and (3) to examine students’ attitudes (e.g., perceived usefulness of gamified activities in reviewing class materials) toward gamified activities in an online learning environment.

Theoretical Framework

The theoretical framework was inspired by literature reviews of gamification studies and self-determination theory (SDT) (Deterding, 2011; Dicheva et al., 2015; Hamari et al., 2014; Kim et al., 2017; O’Donnell et al., 2017; Seaborn et al., 2015; Simões, Redondo, & Vilas, 2013; Wilson et al., 2009). This integrated framework was used to design the online gamified activities and guide our study. Based on the literature, gamification elements (e.g., feedback, challenge, rewards, and objectives) may contribute to improved academic performance. Moreover, the “competence” concept from the SDT (i.e., the need to feel that one’s behavior is effective) that is theorized as increasing intrinsic learning motivation was evaluated in the present study in the sense that we investigated whether the competence gained from an online course can be enhanced when students have opportunities to learn skills and be challenged in

proper ways through gaming, as well as receive informational and positive feedback (Forde, Mekler, & Opwis, 2015; Ryan & Deci, 2000).

Methods

This study employed an experimental research design with the random assignments of participants to the experimental and control groups. We examined students' academic performance, perceived competency in statistics, and perceived engagement before and after the implementation of gamified activities. Moreover, students' perceptions of the usefulness of gamified activities were observed.

Though several studies have argued that gamification could be a great teaching tool across multiple disciplines, challenges for effective implementation still exist. Due to different approaches in gamification applications based on the interests and needs of various fields, it is still quite challenging to provide successful online gamified environments to enhance academic performance and increase learning motivation and student engagement (Dicheva et al., 2015; Kapp, 2012). Therefore, we identified commonality among the fundamental elements of gamification based on gamification theories (Deterding et al., 2011; Kappen & Nacke, 2013; Harari et al., 2014; Seaborn et al., 2015) and integrated them into the present study. The gamified activities included major key gamification elements (e.g., points, leaderboards, progression, status, levels, and rewards).

Two well-designed online educational games, "Concept Review Bingo" and "Jeopardy Exam Review," were implemented in a graduate-level statistics course. These online versions of bingo and *Jeopardy* games were designed using the wiki format that is usually a built-in feature in any LMS. A *wiki* is "an expandable collection of interlinked Web 'pages', a hypertext system for storing and information—a database, where each page is easily editable by any user with a form-capable Web Browser clients" (Leuf & Cunningham, 2001, p. 14). In other words, a wiki can be a collaborative tool that allows students to create web contents (e.g., web pages, texts, and tables). For the present study, we used the built-in wiki setting in the LMS to create an editable contingency table (i.e., a 4 x 4 table [bingo] or a 6 x 5 table [*Jeopardy*]), where each cell contained a short essay or statistical calculation question.

One of the special characteristics of the gamified activities was to have students submit their answers in a game setting, such as online bingo or *Jeopardy*. Both gamified activities required players to provide their answers into a wiki-based table through an online course LMS. By default, only one student in a course could log in to edit the wiki table, while everyone else would have their access to the wiki table blocked until the student logged out. This mechanism created a natural first-come, first-choice environment, which fits the competition and challenge element in the gamification design. Most LMS companies provide some forms of wiki capabilities to higher education institutions.


"Concept Review Bingo" served to review key statistical concepts for exam preparation. The game consisted of 16 questions, which varied in difficulty. The questions were arranged in a 4 x 4 table, as illustrated in Figure 1. Each student was permitted to answer up to four of the questions in the table. Each correctly answered question earned the student one point of extra credit. However, if a student correctly answered four questions across a row, vertically in a column, or diagonally, the student earned a bingo. This resulted in double points for the activity. Because of the first-come, first-choice nature of wikis, students were motivated to submit their answers quickly to claim their questions. Once all 16 questions were answered, feedback was provided to the entire class. Table 1 summarizes the gamification components for "Concept Review Bingo."

Gamify Online Courses With Tools Built Into Your Learning Management System (LMS) to Enhance Self-Determined and Active Learning

Review Bingo: Descriptive Statistics

Edit Wiki Content

Created By  Cheng-Chia B. Chen on Monday, January 22, 2018 5:20:17 PM CST

last modified by  Cheng-Chia B. Chen on Thursday, May 31, 2018 7:12:01 AM CDT

You must type your answers and name (at the same time)!!!

<p>1. Give examples of quantitative and qualitative variables; discrete and continuous variables; and determine the appropriate measurement scale for each.</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>2. Give an example of descriptive statistics. Give an example of inferential statistics.</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>3. Define stem and leaf plot and construct a stem and leaf plot for the following data. In addition, provide a 5-number summary.</p> <p>12 23 30 51</p> <p>12 27 33 42</p> <p>18 24 36 48</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>4. The Swiss physician H.C. Lombard once compiled longevity data for different professions. He used death certificates that included name, age, at death, and profession. He then proceeded to compute the average (mean) length of life for the different professions, and he found that students were lowest with a mean of only 20.7 years! (Read "A Selection of Selection Anomalies" by Wainere, Palmer, and Bradlow in <i>Chance</i>, Volume 11, No.2) Similar results would be obtained if the same data were collected today in the United States. Please analyze the results: Is being a student really more dangerous than being a police officer, a taxicab driver, or a postal employee? Explain.</p> <p><u>Answer:</u></p> <p>Name:</p>
<p>5. What is the difference between a discrete variable and a continuous variable?</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>6. What is the difference between a population and a sample?</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>7. Suppose we randomly select a graduate class in the College of Public Affairs and Administration to do a survey on students' statistical skills based on their statistics profiles. What is a reasonable sample? What is a reasonable population? Can inferences be made to all UIS students or all residents of Illinois? Justify.</p> <p><u>Answer:</u></p> <p>Name:</p> <p>-</p>	<p>8. What is a standard deviation? What does the standard deviation tell you about your data?</p> <p><u>Answer:</u></p> <p>Name:</p>
<p>13. According to the week 2 lecture, why divide by (n-1) instead of by n when we are calculating the sample standard deviation?</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>14. Provide the three distributional shapes (normal, left-skewed, and right-skewed) along with some of their real-life examples. Describe the relationships between mean, median, and mode for each distribution.</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>15. Define each of the following terms: Biostatistics, Descriptive Statistics, and Inferential Statistics. What is the role of biostatistics in public health research and program evaluation?</p> <p><u>Answer:</u></p> <p>Name:</p>	<p>16. An article in the <i>New York Times</i> noted that the ZIP code of 10021 on the Upper East Side of Manhattan is being split into the three ZIP codes of 10065, 10021, and 10075 (in geographic order from south to north) The ZIP codes of 11 famous residents (including Bill Cosby, Spike Lee, and Tom Wolfe) in the 10021 ZIP code will have these ZIP codes after the change: 10065, 10065, 10065, 10065, 10065, 10065, 10021, 10021, 10075, 10075, 10075, 10075. What is wrong with finding the mean and standard deviation of these 11 ZIP codes?</p> <p><u>Answer:</u></p> <p>Name:</p>

Comment

Figure 1. Screenshot of "Concept Review Bingo."

Table 1

Online “Concept Review Bingo” Gamification Elements and Design Principles

Elements of Gamification for “Concept Review Bingo”	Implementation of the Element & Design Principle
Objectives	The goals to review key statistical concepts for exam preparation.
Competition & Challenge	Students compete to win extra credits and encounter a variety of challenges in the game settings.
Feedback	The feedback (i.e., detailed answers and/or explanation videos) is given after students have answered all questions (an example of shortened feedback cycles).
Points, Rewards, & Leaderboards	Each selected-response question answered correctly is worth one bonus point. If a student has all four correct answers covered diagonally, across a row, and vertically in a column, the student will get a doubled award, which is worth 8 points ($4 \times 2 = 8$).
Levels	Different levels (difficulties) of questions are created.
Platform	Wikis (i.e., a website developed collaboratively by a community of players, allowing any player to add and edit content).
Rules & Customization	Game mechanics and adaptive mechanisms to meet the players’ skill levels and needs.
Storytelling, Theme, & Role-Playing	N/A
Replayability	N/A

Similar to the game mechanics of the long-running *Jeopardy* television show, the online “Jeopardy Exam Review” consisted of six categories of topics. Each category included five questions ranging in difficulty (see Figure 2). The “dollar” value earned with each correct answer increased as the question’s difficulty increased (see Figure 3). After the end of the “Jeopardy Exam Review” game, we provided instructional videos for each question with thorough explanations for the gamified questions (see Figure 4). The “Jeopardy Exam Review” demonstrates different game mechanics and structures than the “Bingo Concept Review.” Its elements and design principles are listed in Table 2.

Gamify Online Courses With Tools Built Into Your Learning Management System (LMS) to Enhance Self-Determined and Active Learning

MPH 503 Biostatistics - Jeopardy Exam Review

Rules
You will be able to see the questions by clicking on the dollar amount. Please type your answers and your name (at the same time) in the corresponding box below (see example) after clicking on "Edit Wiki Content" tab. Then, remember to click on "submit" tab to complete the editing.

Each student can answer **any** questions that are not answered by other students. If you answer the question correctly, you will receive the dollar amount for each question. The rank of the participants will be determined by total dollar amount.

Award (6:00 pm CT on March 28, 2016 to 6:00 pm CT on April 1, 2016)

Extra points will be counted toward your exam 1. If you get all possible points on the exam 1, the extra points will be added to your SPSS lab assignments or problem sets.

First place and Second place: **15 points**

Third place and Fourth place: **10 points**

5 points for everyone who answers at least one question with the correct answer.

Topic 1: Confidence Interval & Hypothesis Testing	Topic 2: Correlation and Regression	Topic 3: Explore Data with Graphics & SPSS Analysis Procedure	Topic 4: Probability & Normal Distribution	Topic 5: Intro to Bio & Descriptive Statistics (I)	Topic 6: Intro to Bio & Descriptive Statistics (II)
<u>\$100</u>	<u>\$100</u>	<u>\$100</u>	<u>\$100</u>	<u>\$100</u>	<u>\$100</u>
<u>\$200</u>	<u>\$200</u>	<u>\$200</u>	<u>\$200</u>	<u>\$200</u>	<u>\$200</u>
<u>\$300</u>	<u>\$300</u>	<u>\$300</u>	<u>\$300</u>	<u>\$300</u>	<u>\$300</u>
<u>\$400</u>	<u>\$400</u>	<u>\$400</u>	<u>\$400</u>	<u>\$400</u>	<u>\$400</u>
<u>\$500</u>	<u>\$500</u>	<u>\$500</u>	<u>\$500</u>	<u>\$500</u>	<u>\$500</u>

Jeopardy Exam Review (I)

[Edit Wiki Content](#)

Created By Cheng-Chia B. Chen on Wednesday, March 9, 2016 4:27:48 AM CST

last modified by Cheng-Chia B. Chen on Wednesday, October 19, 2016 11:23:54 PM CDT

type your answers and name (at the same time) in the corresponding box.

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
<p>\$100</p> <p>A confidence interval estimates a range of values for the population parameter with a level of confidence (c) attached (e.g., 95% confidence that the range or interval contains the parameter).</p> <p>That is correct!!</p> <p>Explanation Video</p>	<p>\$100</p> <p>$SS_T$= Total variability between scores and the mean.</p> <p>SS_T= Total Sum of Squares.</p> <p>That is correct!!</p> <p>Explanation Video</p>	<p>\$100</p> <p>Kurtosis - the measure of whether data are peaked or flat relative to a normal distribution.</p> <p>That is correct!!</p> <p>Explanation Video</p>	<p>\$100</p> <p>Conditional probability means "the probability of A under the condition B."</p> <p>That is correct!!</p> <p>Explanation Video</p>	<p>\$100</p> <p>Biostatistics</p> <p>That is correct!!</p> <p>Explanation Video</p>	<p>\$100</p> <p>A small standard deviation indicates that data points are close to the mean.</p> <p>That is correct!!</p> <p>Explanation Video</p>

Figure 2. Jeopardy Exam Review Screenshot 1: Demonstration of game rules, mechanics, settings, and wiki tables/cells.

Topic 1 for 100 points

It is a range of values for the population parameter with a level of confidence attached.

Figure 3. "Jeopardy Exam Review" Screenshot 2: Demonstration question after clicking the dollar sign.

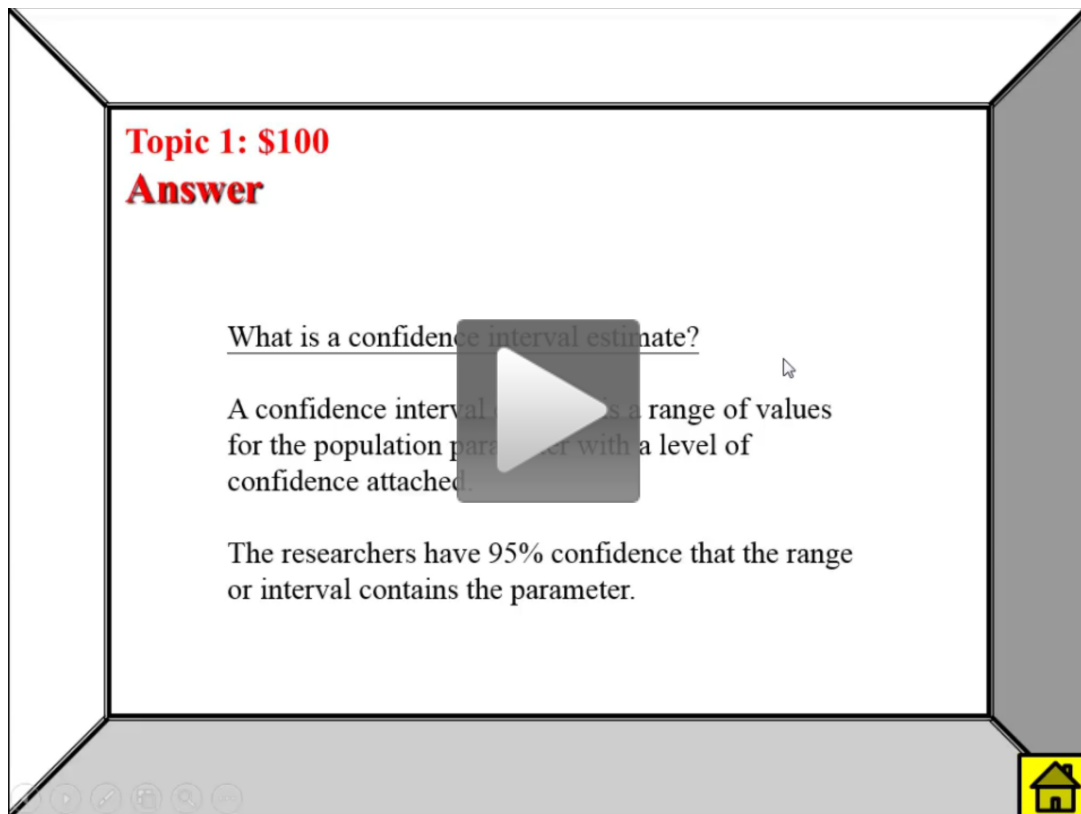


Figure 4. "Jeopardy Exam Review" Screenshot 3: Demonstration of the instructional video that explains detailed solution for the corresponding question.

Table 2

Online “Jeopardy Exam Review” Gamification Elements and Design Principles

Elements of Gamification for “Jeopardy Exam Review”	Implementation of the Element & Design Principle
Objectives	The goals to review key statistical concepts for exam preparation.
Competition & Challenge	Students compete to win extra credits and encounter a variety of challenges in the game settings.
Feedback	The feedback (i.e., detailed answers and/or explanation videos) is given after students have answered all questions (an example of shortened feedback cycles).
Points, Rewards, & Leaderboards	This activity gives students the opportunities to earn extra credits.
Levels	The rows of questions are ranked from easiest to most difficult, with more difficult answers being worth more points (in the form of dollar values).
Platform	Wikis (i.e., a website developed collaboratively by a community of players, allowing any player to add and edit content).
Rules & Customization	Game mechanics and adaptive mechanisms to meet the players’ skill levels and needs.
Storytelling, Theme, & Role-Playing	N/A
Replayability	N/A

Data Collection

The study participants were graduate students who took an online statistics course across two consecutive academic years (2015–2017) from a midwestern university in the United States. The University of Illinois Webtools (with capabilities similar to Qualtrics) were used to set up online survey questions for the study participants. Two different gamified activities (“Concept Review Bingo” and “Jeopardy Concepts Review”) were implemented during fall and spring semesters from fall 2016. “Concept Review Bingo” was played twice for three days while “Jeopardy Concept Review” was played for an entire week during the 16-week semester. The participants ($n = 80$) were randomly assigned to the experimental group (i.e., students with exposure to three gamified events) or the control group (i.e., students without exposure to gamification).

There were 44 students in the experimental group and 36 students in the control group. The academic performance of participants in both the experimental and control groups was compared based on the average of the exam scores (midterm and final exams), as was their statistics competency (evaluated by six self-reported questions). In addition, the pre- and posttest design was applied to the experimental group to examine students’ perceived usefulness and motivation for statistics before and after the implementation of the gamification.

Variables and Measurement

The dependent variables for the present study included academic performance (i.e., the average of all exam scores [maximum 300 points]) and overall statistics competencies. A six-item questionnaire regarding students' statistical competencies with a 5-point Likert scale measurement approach was used. The instrument was inspired by the Master of Public Health (MPH) Core Competency Model initiated and created by the Association of Schools and Programs of Public Health. More specifically, a five-level measure of statistics competency (0 = *not confident*, 1 = *a little confident*, 2 = *somewhat confident*, 3 = *highly confident*, 4 = *extremely confident*) was used. Moreover, several students' perceptions of the usefulness of gamification and selected gamification components (e.g., rules, objectives, competition, and challenge) were surveyed.

Statistical Analysis

The dependent variable in both the experimental and control groups was academic performance. Since the normality assumptions for parametric analyses in both experimental and control groups were not satisfied, Welch's *t*-test was used to compare the differences between the group mean exam scores. For gamification-related dependent variables in the experimental group that used pre- and posttest experimental design, Wilcoxon tests were used to compare the ranked data from the responses of the Likert-scale survey questions. All data collected were analyzed using IBM SPSS version 24.

Results

Academic Performance

A Welch's independent *t*-test was performed to compare the mean exam scores of the control group and experimental group. As predicted, the experimental group ($M = 272.40$, $SD = 8.91$, $n = 44$) had higher scores than the control group ($M = 251.44$, $SD = 10.56$, $n = 36$), $t(68.68) = 4.73$, $p < .001$, two-tailed. This difference favored students who played three different gamified activities to review key concepts (at the .05 level of significance). The results revealed that the experimental group and control group differed in average exam scores. More specifically, students in the experimental group with the implementation of gamification were observed to have higher exam scores, on average, than the control group. The results from Welch's *t*-test can be found in Table 3.

Table 3
Welch's t-test Between Average Exam Scores From the Experimental and Control Groups

	Experimental group with implementing the games ($n = 44$)		Control group without implementing the games ($n = 36$)		<i>t</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	
Exam Scores	272.40	8.91	251.44	10.56	4.73***

* $p < .05$. ** $p < .01$. *** $p < .001$.

Statistical Competencies

Statistical competencies were measured by self-report six questions. Table 4 illustrates the results from the comparison of competencies based on the pretest (before the gamification implementation) and posttest data ($n = 44$) using the Wilcoxon test. All measures of statistical competency increased in the posttest group. The Wilcoxon matched pairs signed-rank tests were conducted to determine whether students agreed that their statistical competencies were increased after they used game-playing activities to review the important concepts and to prepare their exams.

Table 4

Medians and IQR for Pretest Values, Posttest and Difference of Each Statistical Competency

	Pretest Median	Pretest IQR	Posttest Median	Posttest IQR	<i>p</i>
Discuss biostatistics concepts with my colleagues and friends	2.00	2.00	3.00	1.00	< .001
Understand the roles of biostatistics in research and program evaluation	2.00	1.75	3.00	1.00	< .001
Choose the relevant statistical analyses to answer the research questions	2.00	2.00	3.00	1.00	< .001
Make arguments and conclusions based on proper applications of analytical approaches with relevant study designs	2.00	1.75	3.00	2.00	< .001
Interpret tables, graphs, and statistical outputs	3.00	1.00	3.00	1.00	< .001
Make conclusions based on the statistical results	2.00	1.00	3.00	1.00	< .001

IQR indicates interquartile range.

Note. *P* values for differences are from Wilcoxon signed-rank test ($n = 44$)

* $p < .05$. ** $p < .01$. *** $p < .001$.

Engagement

Wilcoxon matched pairs signed-rank tests were conducted to determine whether interest levels were different before and after the exposure of gamified activities. The results indicated that the pretest and posttest medians were not statistically different, as shown in Table 5 ($p > .05$).

Table 5

Medians and IQR for Pretest Values, Posttest and Difference of Engagement

	Pretest Median	Pretest IQR	Posttest Median	Posttest IQR	<i>p</i>
Discussing biostatistics with colleagues and friend	3.00	1.00	3.00	2.00	.19
Exploring public health career opportunities that require statistical skills	3.00	1.00	2.00	2.00	.90
Reading articles about public health in journals	3.00	1.00	3.00	1.00	.16
Majoring in a biostatistics-related field	2.00	2.00	2.00	2.00	.90
Submitting articles to conferences or journals	3.00	2.75	3.00	1.00	.79

IQR indicates interquartile range.

Note. *P* values for differences are from Wilcoxon signed-rank test ($n = 44$)

* $p < .05$. ** $p < .01$. *** $p < .001$.

Perceptions of Usefulness, Learning Motivation, and Enjoyment From the Gamified Activities

We also examined students' perceptions and opinions of gamification at the end of the semester. Seventy-two percent of students agreed that gamified activities were either extremely or highly useful in helping them review and/or understand fundamental concepts. Moreover, 82% of students stated that it would be worth implementing the competitive educational games to facilitate students' learning in other courses. Sixty-eight percent of students indicated that their learning motivation was higher when competing in the class environment and strongly agreed or agreed that they did better on exams because of what they learned with the games. In addition, 83% of students strongly agreed or agreed that they enjoyed participating in game-based learning activities.

Discussion

Our findings indicated that online gamified activities can have a positive impact on learning statistical and math concepts based on the superior academic performance of the experimental group (i.e., students with the exposure of gamification) compared with the control group. This finding was consistent with several recent studies (DeMarcos et al., 2014; Shatz, 2015; Su & Cheng, 2015; Yildirim, 2017) that suggested gamification-based teaching practices help enhance students' academic achievement. For the competence concept borrowed from the self-determination theory and the Association of Schools and Programs of Public Health, results indicated that the students had significantly higher confidence in their perceived statistical competencies. This encouraging finding strengthens researchers' assumption that increased confidence in students' statistical competencies might be associated with better academic performance and learning motivation (Ryan et al., 2000).

Interestingly, there was no difference in student engagement when comparing results between experiment and control groups. In other words, online students with gamified activity experience did not increase their perceived engagement. This finding was not consistent with some previous studies that indicated gamification's positive effect on student engagement (Cózar-Gutiérrez & Sáez-López, 2016; de-Marcos et al., 2017). Although a number of studies found that educational game playing might increase student engagement (Dicheva et al., 2015; Kim et al., 2018), most findings used different measurement methods of engagement that might introduce bias into their results. Moreover, some of their contradictory findings were observed in the traditional on-campus settings instead of online teaching environments.

Furthermore, our study reflects a consistent challenge for educators to transform face-to-face teaching tactics to fit the characteristics and learning needs of online students. Online instructors may need to challenge themselves and employ more instantly interactive gamified learning activities to increase students' engagement. For example, we could use readily available techniques (e.g., mobile apps, chat function in Google Docs to facilitate the effectiveness of collaboration) to expand potential benefits from gamification that might amplify learners' engagement among themselves and between educators and learners.

Several notable findings were observed from the survey results of students' attitudes and perceptions towards their online gamification experiences. Based on our data, a large proportion of students felt that the concept review games were very helpful in strengthening their knowledge of class concepts. In addition, they felt a stronger confidence in their statistical competencies. Moreover, a great number of students mentioned that their learning motivation was higher due to these innovative online gamified activities, and their desire to experience

similar learning environments was very high. These findings are consistent with previous studies (Barata et al, 2013; de-Marcos et al., 2014).

Although most students were positive about gamification, there were some concerns, such as dislike of the competition atmosphere (i.e., dislike of the first-come, first-choice game rule) and time constraints. Student-centered pedagogy and active learning strategies often tend to consider positive and negative thoughts from students to help them learn better. Thus, the small number of complaints about gamification cannot be neglected; different voices regarding gamification need to be taken seriously (Furdu, Tomozei, & Kose, 2017). In summary, our findings support our goals to implement meaningful and effective gamified activities to (1) increase students' academic performance and statistical competencies; (2) enhance engagement and social presence among students and instructors; (3) involve every student in an online learning community to review important concepts that students have learned; and (4) help students ease possible frustration from statistics by giving them additional opportunities to review critical concepts through gamification. Our experiences from the creation of online gamification and its influences in self-determined and active learning may provide a new online teaching strategy to enhance students' academic performance and engagement.

Limitations and Future Research Directions

Though we have learned critical lessons from our findings, the results must be interpreted in light of some limitations. First, students might perceive the researchers' intention to evaluate the effectiveness of the gamification; thus, a certain degree of the Hawthorne effect might have played a minor role in producing a slightly biased outcome. Second, the present study investigated students' perceptions and attitudes toward gamified activities; however, the academic performance aspects that could be influenced by specific gamification attributes (e.g., challenge, goals, and rules) were not individually evaluated. Third, the learning-related influence from gamification was measured in a 16-week course; therefore, the generalizability of findings to any other postsecondary course is limited.

For future studies, a double-blind experimental design could be used to decrease the likelihood of the Hawthorne effect. Researchers could isolate the effects from different gamification components and examine their individual influence on academic performance and students' feedback. Furthermore, cultural influences on effectiveness and acceptance of online gamified learning experiences and settings might be another area to explore.

Conclusions

The present study was one of the first studies to examine students' academic performance following an innovative application of online gamification from existing LMS collaborative tools. Well-designed gamified activities with proper implementation could enhance online students' academic performance. In addition, students with meticulously planned gamification experiences demonstrated their fondness for these useful games that increased their professional competencies.

These findings may contribute to the existing literature on how gamification-based teaching strategies might play an important role in enhancing online learning effectiveness, increasing students' learning motivation. Moreover, our gamification design that allowed online students to answer questions by co-editing a wiki table had the advantage of taking care of online students' needs for both asynchronous and synchronous learning. Finally, the gamification designs and mechanics that use built-in LMS collaborative tools may help overcome game implementation barriers, such as high game-development costs and the challenge of aligning learning objectives perfectly with existing educational games.

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Strengths-Based Analysis of Student Success in Online Courses

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Abstract

Online courses today give a broad, diverse population access to higher education. Despite postsecondary institutions embracing this opportunity, scholarly literature reveals persistent concern over low retention rates in online courses. In response to this concern, an explanatory sequential, mixed methods study was conducted in three phases at a public research university to simultaneously explore personal, circumstantial, and course variables associated with student success from a strengths-based perspective. In Phase One, existing data on student enrollments across four years were analyzed. During Phase Two, a subset of Phase One students from a single semester was invited to complete an assessment of noncognitive attributes and personal perceptions, followed in Phase Three by interviews among a stratified sample of successful students from the previous phase to elaborate on factors impacting their success. Quantitative analyses identified seven individual variables with statistical and practical significance for online student success. Interestingly, the combination of factors classified as predictive of success changed with student academic standing. The impact of differential success factors across academic experience may explain mixed results in previous studies. The themes that emerged from the interviews with students were congruent with quantitative findings. A unique perspective was shared when students discussed “teaching themselves,” providing additional insight into perceptions of teaching presence not formerly understood. The combination of a more contextual research approach, a strengths-based perspective, and insights from student perceptions yielded implications for educational practice.

Keywords: online learning, online education, student success, student perception, teaching presence, higher education, postsecondary, strengths-based, mixed methods

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Strengths-Based Analysis of Student Success in Online Courses

Enrollment in online courses at degree-granting higher education institutions within the U.S. grew at an exponential rate during the first decade of this century (Allen, Seaman, Poulin, &

Straut, 2016). Between fall 2002 and fall 2011, the compound annual growth rate for U.S. students taking at least one online course was 17.3% (Allen & Seaman, 2013). Since 2011, online enrollments have continued to climb while on-campus enrollments have decreased (Allen et al., 2016). The growth in online learning can possibly be explained by the convergence of several trends. A broader, more diverse population has entered higher education facilitated by advances in technology which allow students to access content anywhere at any time (Herbert, 2006; Layne, Boston, & Ice, 2013). As a result, many higher education institutions have prioritized online education as a strategic approach to increase enrollment (Clinefelter & Aslanian, 2016). At the same time, campaigns promoting the need for more Americans to participate in higher education have emerged both at national and at state levels, prompting more nontraditional students to enroll in postsecondary courses (Carnevale, Strohl, & Smith, 2009; Kelderman, 2013; Soares, 2013). Students who enter college immediately after high school, live on campus, and attend full-time in pursuit of a four-year degree, categorized as *traditional students* (Soares, 2013), are no longer the norm, as most students enrolled in higher education in the U.S. today are, in fact, nontraditional students (National Adult Learner Coalition, 2017).

Meanwhile, fewer campus-based students take face-to-face classes exclusively without including one or more online courses in their class schedules (Allen & Seaman, 2017). A majority of postsecondary universities in the U.S. have therefore embraced online learning as part of their long-term strategy. In fact, more than 60% of chief academic leaders consider online education critical to their institution's long-term strategy. These institutions continue to expand online programs as on-campus enrollments decline (Allen et al., 2016).

Despite rapid enrollment growth and institutional acceptance, many academic leaders express concern over poor retention rates among online students (Allen & Seaman, 2013; Berge & Huang, 2004; Park & Choi, 2009). A number of scholars have reported completion rates among online and distance courses to be significantly lower than for face-to-face courses (Boston, Ice, & Gibson, 2011; Jaggars & Xu, 2010; Lokken, 2017; Rovai, 2003). Higher education is faced with increasing numbers of students enrolling in online courses despite the possibility that they may not complete them. This dilemma represents a waste of resources for both the student and the institution (Simpson, 2006). It is, therefore, essential that colleges and universities understand issues related to student attrition and find ways to improve persistence in online courses (Ekstrand, 2013; Herbert, 2006). The current study addressed this need using a strengths-based perspective to examine student success in online courses.

Review of Related Literature

Much is still unknown about student success in online courses. Scholars have researched postsecondary achievement for decades, but the history of online learning itself is relatively short. During the first decade of this century, online pedagogies evolved as new technologies began to mature. Research into student success in the online environment has not yet coalesced into a strong body of consistent evidence. Many variables contributing to success have only been examined in a single study, while those that have been examined in multiple studies have produced conflicting results (Clark, 2013; Wang, Shannon, & Ross, 2013).

As one example of contradictory results, Cochran, Campbell, Baker, and Leeds' (2014) study of undergraduate students at a large state university found a positive correlation between age and online course completion for two groups: students who did not receive scholarships and those

without student loans. Many other studies found no correlation between age and student success in online courses (Aragon & Johnson, 2008; Baturay & Yukselturk, 2015; Gibson, Kupczynski, & Ice, 2010; Guidry, 2013; Harrell & Bower, 2011).

A second example of antithetical results related to race or ethnicity. Several studies found no relationship with student success in online learning (Aragon & Johnson, 2008; Gibson et al., 2010; Harrell & Bower, 2011; Jost, Rude-Parkins, & Githens, 2012). Some, however, found race combined with other factors yielded a significant association with success (Cochran et al., 2014; Rockinson-Szapkiw, Wendt, Wighting, & Nisbet, 2016; Suphi & Yaratana, 2012).

In addition to the problem of conflicting evidence discussed above, meta-analyses reveal that studies to date show little consistency in factors considered and approaches used. Some scholars, for example, have approached online student outcomes by studying dropout factors, while others have examined persistence factors (Hart, 2012; Lee & Choi, 2011). With regard to the inconsistency in factors examined, Lee and Choi (2011) reviewed scholarly research published between 1999 and 2009, looking for empirical data on variables that influence students' decision to drop out of postsecondary online courses. They identified a wide variety of 69 factors, typically investigated in isolation. The authors further proposed categorizing these variables into three broad categories—student factors, course/program factors, and environmental factors—and addressed in their conclusions the need for future studies to address interrelationships between these three clusters, as opposed to narrow, independent evaluations of a single type of variables.

In contrast to Lee and Choi's (2011) focus on dropout factors, Hart (2012) conducted an integrated literature review of articles published between 1999 and 2011 that addressed students' ability to persist in online courses. Similar to Lee and Choi's (2011) conclusions about interrelationships, Hart noted that persistence is a complex variable that may not be directly related to knowledge acquisition at all. A student's decision to persist may be influenced by a combination of factors both internal and external to the university, such as personal motivation, time to graduation, communication with the instructor, and family support.

Glazier's (2016) review of scholarly work described three broad categories of explanations for the lower success rates of online courses compared to classroom courses: (a) student characteristics, including both demographics and academic preparedness; (b) the student's environment; and (c) course design and interaction. Few studies to date have examined these three categories in combination. Researchers who did look at all three addressed student satisfaction with the course but did not include variables of course design and interaction (Baturay & Yukselturk, 2015; Levy, 2007; Wang et al., 2013). Studies that evaluated course design and interaction typically did not include independent variables of students' personal characteristics and circumstances (Hegeman, 2015; Jagers & Xu, 2010; Liu, Gomez, & Yen, 2009; Olson & McCracken, 2014). Evaluating personal, circumstantial, and course factors simultaneously requires a more complex research design. While some of these data are most reliable when retrieved from official university information systems, others require asking students directly. Noncognitive attributes and perceptions, in particular, necessitate a carefully designed assessment tool.

The rationale for considering all three variable types together aligns with the sustainable student retention model proposed by Berge and Huang (2004). This theoretical model was built as a framework allowing institutions to add variables to three clusters (personal, circumstantial, and institutional), and to prioritize the relative importance of the three areas within the institutional

context (Berge & Huang, 2004). This theoretical framework was adapted for the current study by changing institutional variables to course variables. Because the same institution delivered all course enrollments included in this research, there were no differing institutional variables to consider. Course-specific elements were examined instead, as a subset of institutional characteristics.

Examining the reasons students leave college applies a pathology-based approach to the problem (Shushok & Hulme, 2006). Strengths-based approaches, on the other hand, attempt to identify “what is right” with students rather than diagnosing “what is wrong” (Lopez & Louis, 2009; Shushok & Hulme, 2006; Stebleton, Soria, & Albecker, 2012). Moreover, deficit-based research often separates people from the context in which they live, while strengths-based research promotes an ecological view of the relationship between subjects and their circumstances (Maton et al., 2004). This implicit emphasis on context made the strengths-based perspective a natural choice for the current study.

The strengths-based perspective originated in the field of social work as an alternative to the deficit-based focus on dysfunction. Saleebey (2006) articulated a number of underlying principles of the strengths perspective, including the belief that “every individual, group, family, and community has strengths” (p. 16). Although strengths-based practice acknowledges problem behaviors, solutions are pursued by highlighting the individual’s competencies, resources, and values (Shaima & Narayanan, 2018). Basic tenets of this perspective align with the field of positive psychology, which focuses on the study of strengths, well-being, and optimal functioning (Lee Duckworth, Steen, & Seligman, 2005). Proponents from a variety of fields have embraced these ideals in support of social justice, racial equity, and cultural inclusion (e.g., Craven et al., 2016; Dew, Anderson, Skogrand, & Chaney, 2017; Fenton, Walsh, Wong, & Cumming, 2014; Stebleton, Soria, & Albecker, 2012; Veney et al., 2016; Watt, Norton, & Jones, 2013).

Purpose and Significance of the Study

The current study, including both undergraduate and graduate students, was undertaken to understand factors associated with student success, with the goal of supporting persistence and increasing educational attainment. In applied practice, strengths-based approaches seek to understand and build upon the strengths of an individual or group. However, prior to applying strengths-based assessments or interventions, it is necessary to understand, through research, which characteristics might be perceived as strengths. For example, before publishing the Clifton StrengthsFinder as an assessment tool, Clifton and his colleagues identified thoughts, feelings, and behaviors associated with situational success by studying top performers in a variety of roles and settings (Asplund, Lopez, Hodges, & Harter, 2007). Likewise, Shushok and Hulme (2006) assert that the first step toward implementing a strengths-based approach on a college campus is to study and understand successful students. Strengths-based research does not ignore those who may be considered unsuccessful, but it begins with a focus on those who are successful to first learn the proper variables of interest.

An explanatory sequential, mixed method design was selected to complement the strengths-based approach. By definition, explanatory sequential research begins with quantitative measures and continues with qualitative (Cresswell, 2011). Because the literature review yielded contradictory evidence, this study sought an opportunity to explain results from the quantitative phases in more depth through qualitative follow-up. Data collection and analysis proceeded sequentially: quantitative methods were used to examine correlation between 28 variables and

student success in online courses. Qualitative methods were subsequently employed to explain and elaborate on factors identified through quantitative means. Qualitative interviews captured the voices and viewpoints of successful students. The current study addressed five related questions:

1. To what extent do personal variables, circumstantial variables, or course variables account for student success in asynchronous online courses?
2. To what extent can a combination of personal, circumstantial, and course variables be used to predict success in asynchronous online courses?
3. How do successful online students perceive the impact of personal, circumstantial, and course variables in their educational experience?
4. How do successful online students define their role versus the instructor's role, and how do they believe each role contributes to student success?
5. How have successful online students been able to overcome challenges and persist to completion?

Personal, circumstantial, and course variables examined in this study are listed in Tables 1 and 2.

Methods

Study Setting and Population

The current investigation was conducted in three phases at the University of Alaska Fairbanks (UAF), a public doctoral university whose primary campus is located in interior Alaska. UAF serves nearly 10,000 students, 88% of whom are undergraduates. One distinctive characteristic of this institution is the breadth of credentials granted: UAF offers workforce development and vocational programs, as well as baccalaureate degrees, master's degrees, and PhDs. In other words, the public community college mission is embedded within this university. The range of degree levels offered by this single university provided an opportunity to explore success factors across the academic spectrum.

This study examined students who took online courses via UAF eLearning. The eLearning unit is responsible for supporting all asynchronous online courses offered through UAF academic departments. More than 25 eLearning staff members provide centralized instructional design, faculty development and support, enrollment management, and student services for online courses and programs. Limiting the study to eLearning-supported courses ensured many aspects of the course design, delivery, and support were consistent, resulting in a more controlled analysis of variables. Phase One began by examining the archived records of all students who took online courses through UAF eLearning over the course of four academic years (fall 2011 through spring 2015). Students included in this research were located across the state and beyond, as shown in Figure 1.

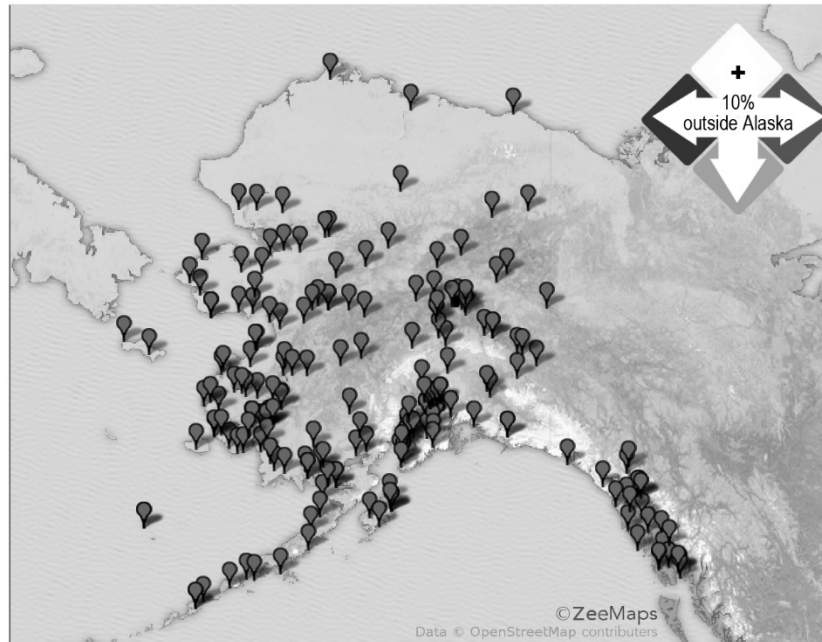


Figure 1. Student locations within Alaska. Map created with ZeeMaps and used by permission.

Pursuant to the explanatory sequential design, the list of participants was narrowed in each phase to provide tighter focus and support additional data collection. Figure 2 depicts the sequence and scope for each of the three phases.

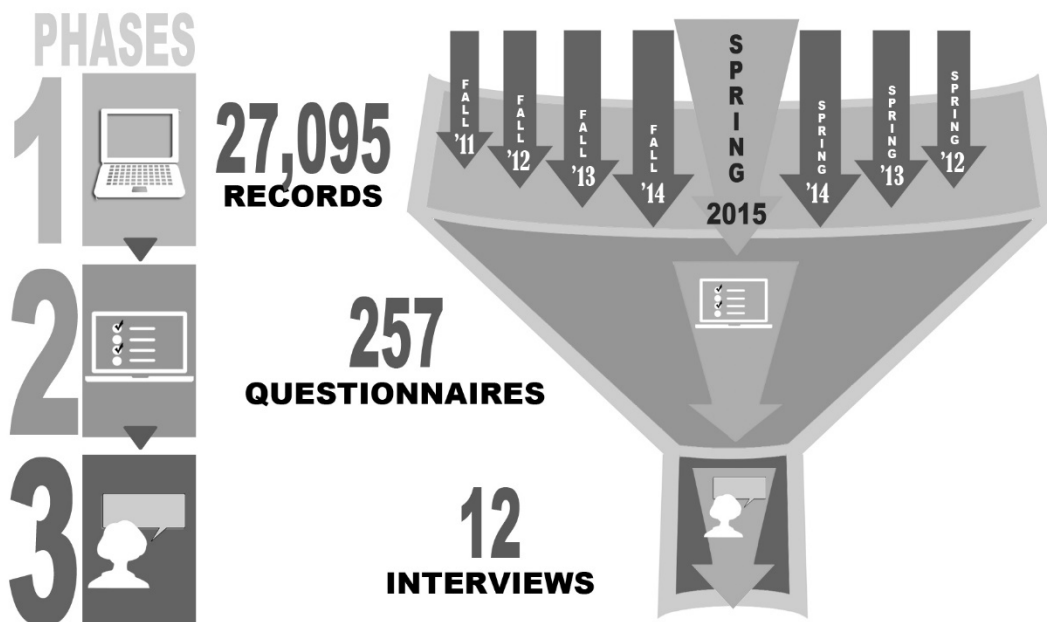


Figure 2. Research conducted in three phases using an explanatory sequential design.

Phase One participants. The first phase of research examined 27,095 enrollments, each defined as a distinct student within a specific course for a given semester. This was not 27,095 unique students but rather distinct student-course-semester combinations. Each case, therefore, represented a distinct combination of course, circumstantial, and personal variables.

Phase Two participants. Participants in Phase Two included enrollments from the latest semester in the Phase One dataset, with the expectation that students might recall details more vividly for the most recent semester. While Phase One used archived data, Phase Two queried participants for additional information, using perspectives drawn from psychology, sociology, and education. All 2,581 students having taken fully online courses in spring 2015 were invited to complete a questionnaire. In contrast to Phase One, which included every enrollment, in Phase Two all students were invited to participate once, regardless of how many online courses they took during the spring 2015 semester. Forty percent of the spring 2015 students took more than one online course that semester; for these students the invitation indicated the course randomly selected for inclusion in the study.

Phase Three participants. Candidates for Phase Three were identified from the list of successful students who completed the Phase Two questionnaire. Because Phase One analyses revealed differential predictors of success across class standing, a stratified random sample was drawn for Phase Three that included two students from each class standing. The random sample was not constrained to stratify for gender, because Phase One analyses revealed no association between gender and success. In total, 12 students were interviewed, including 10 females and two males.

Phase One Data Collection and Analyses

The definition of student success for Phase One was operationalized as a final course grade of C- or higher, because UAF academic regulations recognize C- as the minimum passing grade that signifies sufficient mastery to advance in the academic sequence. Each case was then coded as either a successful or unsuccessful course completion. Archived data for all online students were retrieved from the University of Alaska student information system. Informed by the evidence-based theoretical framework selected (Berge & Huang, 2004), extracted data were clustered into categories of personal, circumstantial, and course variables. The summary presented in Table 1 outlines the classification of Phase One variables by category and by whether they were dichotomous, nominal, or ordinal.

Table 1.

Phase One Independent Variables

Personal Variables	Circumstantial Variables	Course Variables
● Gender	● First-time eLearning Student	■ Course Level
● UA Scholar	● eLearning Courses Only	■ Class Size
● International Student	● Full-time Student	
● Active Military	● Degree Level	
● UA Athlete	● Financial Aid	
● Race	● Location	
■ Age	● Class Standing	
■ Cumulative GPA		

Key:
 ● = dichotomous
 ● = nominal
 ■ = ordinal

Note. UA refers to University of Alaska.

Data analyses. Variables were analyzed for association with student success by means of Crosstabulations with chi-square tests for independence. Cramér's *V* was used to evaluate effect size. Logistic regression was then used to examine whether a combination of the 17 variables could be used to predict success. The fact that many students were successful in some courses and unsuccessful in others underscored the importance of evaluating personal, circumstantial, and course variables in combination. Data analyses were performed using SPSS, version 22. A significance level of .05 was used in all statistical tests.

The general regression model used was (Gordon, 2015):

$$\text{Logit}(\hat{Y}) = b_0 + b_1X_1 \dots b_{17}X_{17} \quad (1)$$

Where \hat{Y} is success, X_1 is gender, X_2 is UA Scholar, X_3 is international student, X_4 is active military, X_5 is UA athlete, X_6 is race, X_7 is age, X_8 is cumulative grade point average, X_9 is first-time eLearning student, X_{10} is eLearning courses only, X_{11} is full-time student, X_{12} is degree level, X_{13} is financial aid, X_{14} is location, X_{15} is class standing, X_{16} is course level, and X_{17} is class size.

Phase Two Data Collection and Analyses

Additional information was collected in Phase Two by means of an online questionnaire. The Phase Two instrument included three nonscale questions targeting circumstantial variables and 60 scale questions designed to measure noncognitive motivational factors and student perceptions, using questions from the following instruments with permission of the authors:

1. Perceived Academic Control (PAC) developed by Perry, Hladkyj, Pekrun, and Pelletier (2001).
2. The General Self-Efficacy Scale (Schwarzer & Jerusalem, 2009). For use in this study, questions were reworded to provide an academic focus.
3. Theories of Intelligence Scale—Self Form for Adults (Dweck, 2013).
4. Multidimensional Scale of Perceived Social Support (MSPSS) developed by Zimet, Dahlem, Zimet, and Farley (1988).
5. Teaching Presence, from the Community of Inquiry (CoI) model (Garrison, Anderson, & Archer, 2000).
6. Social Presence, from the CoI model (Garrison et al., 2000).

A practical question arose when combining these scales into a single instrument: whether to keep the questions grouped (i.e., locus of control questions grouped together, self-efficacy questions grouped together, etc.) or whether to mix the questions randomly. A second, related question was whether to use the scale values from the original instruments or modify the values to be the same throughout the questionnaire. Results of preliminary exploration supported the decision to randomize questions and make scale values consistent. Questions included in the Phase Two instrument are included in the Appendix.

Data analyses. Because these scales had not previously been used together in a single assessment, exploratory factor analysis (EFA; Williams, Brown, & Onsman, 2010) was used to examine scale structure and the relationship between variables. Eight factors were identified from the questionnaire responses. A total scale score was calculated for each participant for each of the eight factors, using the total of constituent question scores. Visual examination of the histogram for each scale—using each participant’s total score—revealed that responses on all eight scales were negatively skewed:

- PAC: skewness of -1.315 ($SE = 0.152$) and kurtosis of 1.805 ($SE = 0.303$)
- Self-Efficacy: skewness of -0.738 ($SE = 0.152$) and kurtosis of 0.546 ($SE = 0.303$)
- Incremental Theory Mindset: skewness of -0.553 ($SE = 0.152$) and kurtosis of -0.191 ($SE = 0.303$)
- Perceived Social Support of a Special Person: skewness of -1.546 ($SE = 0.152$) and kurtosis of 1.666 ($SE = 0.303$)
- Perceived Social Support of Friends: skewness of -0.593 ($SE = 0.152$) and kurtosis of -0.202 ($SE = 0.303$)
- Perceived Social Support of Family: skewness of -0.871 ($SE = 0.152$) and kurtosis of 0.637 ($SE = 0.303$)
- Teaching Presence: skewness of -0.952 ($SE = 0.152$) and kurtosis of 0.649 ($SE = 0.303$)
- Social Presence: skewness of -0.223 ($SE = 0.152$) and kurtosis of -0.409 ($SE = 0.303$)

Due to the nonparametric distribution, the mean value of each participant’s scale scores were therefore categorized with binary values of high or low on each scale. Mean scale scores of 4.0 to 5.0 were categorized as *high*, while scores below 4.0 were classified *low*. Nonparametric techniques were also used on all subsequent analyses. Table 2 displays the resulting Phase Two variables, including the eight scales and three additional (nonscale) variables.

Table 2.

Phase Two Independent Variables

Personal Variables	Circumstantial Variables	Course Variables
<ul style="list-style-type: none"> ● High Perceived Academic Control 	<ul style="list-style-type: none"> ● Parent was College Graduate 	<ul style="list-style-type: none"> ● High Teaching Presence
<ul style="list-style-type: none"> ● High Self-efficacy 	<ul style="list-style-type: none"> ● Employment 	<ul style="list-style-type: none"> ● High Social Presence
<ul style="list-style-type: none"> ● High Incremental Theory Mindset 	<ul style="list-style-type: none"> ● Significant Time/Effort Caring for Family ● High Perceived Social Support of a Special Person ● High Perceived Social Support of Family ● High Perceived Social Support of Friends 	<p>Key:</p> <ul style="list-style-type: none"> ● = dichotomous ● = nominal

Focus on success. The original intent was to compare responses of successful and unsuccessful students in Phase Two. However, an evaluation of Phase Two data revealed a disproportionate number of responses from students categorized as *successful*, with a final course grade of C- or higher. The low rate of return from the nonsuccess group (only 41 out of 303 participants) limited the likelihood of drawing statistically significant conclusions about students who did not complete their online course successfully. Therefore, in alignment with the strength-based approach, analyses focused on responses from successful students, using the ordinal level of final course grade rather than binary measure of success/nonsuccess. Five participants were subsequently removed who had received a “P” (pass) grade. Analyses for Phase Two proceeded with the 257 respondents who earned final course grades of C- to A+.

Crosstabulations were used to assess the distribution of Phase Two variables across final grade categories. Somers’ delta was chosen to assess strength and direction of the association. High scale scores with a statistically significant correlation to final grade were subsequently assessed by means of Mann-Whitney U tests.

Phase Three Data Collection and Analyses

During Phase Three, 12 individual interviews were conducted, recorded, and transcribed. Questions used in the interview protocol were informed by an earlier pilot study. NVivo qualitative data analysis software supported a two-stage process of coding and analysis. During the first cycle, aligned with methods described by Saldaña (2009), provisional coding was used to highlight sections of interview transcripts related to quantitative variables in the first two phases. Provisional coding was congruent with the explanatory sequential research design, creating a natural transition between quantitative and qualitative phases of research. Furthermore, the use of provisional coding formed the foundation for holistic, combined analysis of data from all three phases.

Upon completion of provisional coding, elaborative coding was used to corroborate the theoretical framework of personal, circumstantial, and institutional variables, and to expand on the concept of student roles versus instructor roles that emerged from the pilot of potential interview questions. Elaborative coding enabled identification of additional themes and offered an opportunity to capture illustrative phrases in the participants' own words, which was central to the strengths-based research design. Following qualitative analysis, results from all three phases were considered comprehensively.

Results

Three phases of data collection and analysis were completed sequentially. Participants in Phase Three were a subpopulation of Phase Two, which was a subpopulation of Phase One. Slightly more than half (52.9%) of the total cases studied were full-time students. More than one third were taking online courses exclusively, while 62.2% took a combination of online and face-to-face courses. Basic demographic information for participants in all three phases is displayed in Table 3.

Table 3.

Demographic Description of Participants

Variable	Phase One		Phase Two		Phase Three	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
Gender						
Female	18,334	67.7	179	69.6	10	83.3
Male	8,761	32.3	78	30.4	2	16.7
Race						
Undisclosed	7,903	29.2	66	25.7	2	16.7
Asian	579	2.1	5	1.9	0	0.0
Black	826	3.0	4	1.6	0	0.0
Hawaiian/Pac. Island	183	0.7	2	0.8	0	0.0
Native/Indian	3,739	13.8	28	10.9	1	8.3
White	13,865	51.2	152	59.1	9	75.0
Age						
Under 20	3,378	12.5	40	15.6	5	41.7
20–24	9,586	35.4	89	34.6	2	16.7
25–29	5,010	18.5	50	19.5	2	16.7
30–39	5,509	20.3	42	16.3	2	16.7
40–49	2,324	8.6	22	8.6	1	8.3
50 and over	1,288	4.8	14	5.4	0	0.0
Class Standing						
Non-degree-seeking	2,728	10.1	22	8.6	2	16.7
First-time freshman	1,080	4.0	3	1.2	0	0.0
Freshman, not first time	4,197	15.5	26	10.1	2	16.7
Sophomore	5,306	19.6	47	18.3	2	16.7
Junior	5,251	19.4	51	19.8	2	16.7
Senior	7,504	27.7	74	28.8	2	16.7
Graduate student	1,029	3.8	34	13.2	2	16.7
Degree Level						
Non-degree-seeking	2,728	10.1	22	8.6	2	16.7
Occupational endorse. Certificate	125	0.5	1	0.4	0	0.0
Associate	1,369	5.1	7	2.7	1	8.3
Bachelors	6,496	24.0	35	13.6	0	0.0
Post-bac./licensure	15,345	56.6	158	61.5	7	58.3
Master's	154	0.6	2	0.8	1	8.3
PhD	800	3.0	29	11.3	1	8.3
	78	0.3	3	1.2	0	0.0
Total Cases = 27,095						
			257		12	

Table 4.

Course Characteristics

Variable	Phase One		Phase Two		Phase Three	
	<i>n</i>	%	<i>n</i>	%	<i>n</i>	%
Course Level						
Developmental	414	1.5	1	0.4	0	0.0
Lower	19,002	70.1	152	59.1	6	50.0
Upper	6,413	23.7	63	24.5	3	25.0
Professional	139	0.5	0	0.0	0	0.0
Graduate	1,127	4.2	41	16.0	3	25.0
Class Size						
Less than 15	3,897	14.4	48	18.7	4	33.3
15–30	11,636	42.9	107	41.6	5	41.7
31–45	7,356	27.1	66	25.7	2	16.7
46–60	2,501	9.2	21	8.2	1	8.3
More than 60	1,705	6.3	15	5.8	0	0.0
High Teaching Presence						
Yes			137	53.3	2	16.7
No			120	46.7	10	83.3
High Social Presence						
Yes			83	32.3	2	16.7
No			174	67.7	10	83.3
Total Cases =		27,095	257		12	

Phase One Results

Five of 17 variables collected in Phase One and displayed in Table 1 showed statistical and practical association with student success as measured by crosstabulations with chi-square tests for independence and Cramér's V analysis of effect size (Table 5). Cumulative GPA produced the largest effect size, $\chi^2(4, n = 26,538) = 5,909.55, p = .000$, Cramér's V = 0.47.

Table 5.

Chi-Square and Cramér's V Among Significant Phase One Variables

	Pearson Chi-Square	<i>df</i>	Asymp. Sig. (2-sided)	Cramér's V
Cum. GPA (personal)	5,909.549	4	.000	0.472
Class Standing (circumstantial)	595.660	6	.000	0.148
Course Level (course)	494.101	4	.000	0.135
Degree Level (circumstantial)	342.947	7	.000	0.113
Race (personal)	323.448	5	.000	0.109

Binomial logistic regression revealed cumulative GPA as a significant predictor of student success. Entry of cumulative GPA into the logistic regression model significantly improved model fit (null $-2LL = 31124.25$, $\chi^2 = 5766.33$, $p < .001$). As displayed in Table 6, odds of student success in an online course increased with each categorical level of cumulative GPA.

Table 6.

Logistic Regression Results, Predicting Odds of Success Based on Cumulative GPA

	B	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for OR	
							Lower	Upper
Cum. GPA			4368.026	4	.000			
Cum. GPA 1.00–1.99	.750	.112	44.637	1	.000	2.116	1.698	2.637
Cum. GPA 2.00–2.99	2.309	.099	543.496	1	.000	10.060	8.285	12.215
Cum. GPA 3.00–3.99	3.809	.100	1445.662	1	.000	45.107	37.066	54.893
Cum. GPA 4.00	4.507	.140	1040.385	1	.000	90.684	68.957	119.256
Constant	-1.844	.097	364.111	1	.000	.158		

Further analyses explored whether a combination of variables could be used to predict success. To do so, the dataset was divided into subgroups by class standing to address issues of multicollinearity and mutual exclusion (e.g., class standing and degree level; associate-level degree program and graduate level courses). Logistic regression analyses were conducted for each

class-standing group, using the forward conditional entry method. Figure 3 summarizes logistic regression results and the variance explained by each model, revealing that variables contributing to student success differed by class standing. For nondegree students, a five-factor model (cumulative GPA, gender, race, first-time eLearning, and eLearning courses exclusively) explained 12.9% of variance, increasing accurate classification of cases from 65.2% to 78.1%. For first-time freshmen, a three-factor model explained 17.8% of variance in accurate classification. Improvements in classification of success showed subsequent decline for each successive class standing group. Although the three-factor model for graduate students produced a statistically significant result, the variance explained was too small to be practically significant.

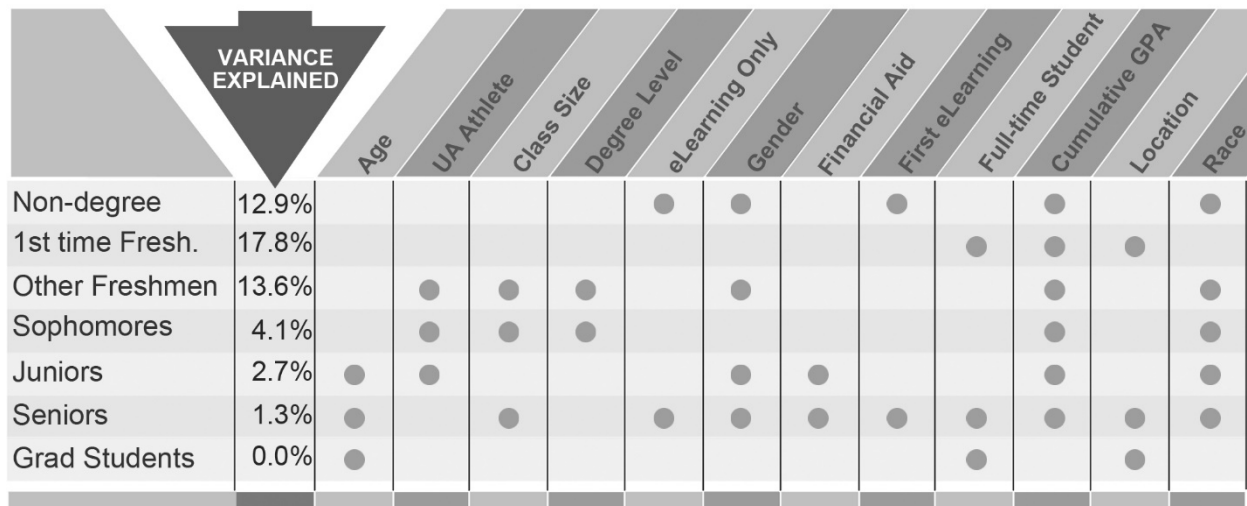


Figure 3. Summary of logistic regression results and the variance explained by each class-standing model.

Phase Two Results

Of the 2,581 students invited to participate in Phase Two, 320 submitted the questionnaire, producing a response rate of 12.4%. After removing 17 responses due to errors or incongruity, EFA was performed to create a factor structure. Initial extraction using principal axis factoring (PAF) produced 10 factors with eigenvalues above 1.0. After visual examination of the scree plot, eight factors were retained. Cronbach’s alpha provided evidence of good internal consistency for each of the eight factors, with alpha scores ranging from 0.83 to 0.97. The final list of eight scale-based variables and three nonscale variables were displayed in Table 2. As previously discussed, low response rate from unsuccessful students led to an adjustment in the research design. The remaining Phase Two analyses were conducted on responses from 257 students who earned final course grades of C- to A+. With this change, the criterion variable became final course grade rather than success/nonsuccess.

Three scale factors were found statistically significant, as presented in Table 7. High perceived academic control (PAC) showed the greatest effect size, explaining 30% of the variation in final grade. The five remaining scale factors, as well as three nonscale variables, failed to reveal a statistically significant association with final course grade.

Table 7.

Somers' Delta Results

	Somers' d	Approx. Sig.
High PAC	.299	.003 *
High Teaching Presence	.181	.007 *
High Social Support of Special Person	.161	.048 **

* significant at the $p < .01$ level. ** significant at the $p < .05$ level

In subsequent Mann-Whitney U tests (Pallant, 2013), significance was confirmed for the scales of PAC and teaching presence. Final grades among students with high PAC (mean rank = 134.38) were significantly higher than among students with lower PAC (mean rank = 95.94), ($U = 2788.000$, $z = -3.013$, $p = .003$). Final grades among students who reported high teaching presence (mean rank = 139.87) were significantly higher than among students who reported lower teaching presence (mean rank = 116.59), ($U = 6730.500$, $z = -2.623$, $p = .009$).

Phase Three Results

Six strong themes emerged during coding and analysis of Phase Three interviews. Themes are described below, using exemplar quotes. While pseudonyms have been used to protect individual identity, general demographics and course characteristics are included in Tables 3 and 4.

Time management. Each participant considered time management critical to success in online courses. Many tied time management to scheduling. As Debra explained, in a face-to-face class the schedule is set for you: “You have to be at class from 9:00 am until noon, and during that three-hour block that’s where you are. You’re in class.” Whereas, online, “you have the entire week to figure out your time allotment of what you’re going to do and how and when.”

Chloe, Gina, and Laura all described their use of student planners to manage homework and deadlines. Ingrid and Karen talked about creating master calendars of assignments and due dates. Beth blocked off time each morning and worked on her online course as if she were attending a class in person. Chloe set aside a specific day each week to complete online course assignments. In addition to scheduling and time allocation, participants linked time management with organization and prioritization.

Supportive family. All interviewees acknowledged the importance of family support. As a single mom, Haley recognized her parents and sister, saying, “They’ll watch my kids while I go take the proctored exams or even just for me to read homework in silence.” Debra and Janet both mentioned husbands picking up additional household responsibility, such as cooking meals. Karen described the power of encouragement, saying, “Maybe you have this passing thought in your head that you think it’s not possible, but you have your parents or your family saying, ‘you can do this, you absolutely can.’”

Teaching presence. All interviewees felt the role of the instructor was vital to student success. The vast majority expressed appreciation for quick instructor response to their emails. Janet commented that instructor feedback made the course feel more personal. Haley thought the addition of media enhanced teaching presence, especially if it included the instructor's own voice. She said, "I feel like that shows a professor really cares that you're learning what they're trying to teach you rather than just relying on the book to teach you." Likewise, Ingrid reflected on the absence of recorded lectures by saying, "It's just 'do this stuff for your grade.' You're just reading from the textbook or watching other things that aren't the professor. It's really hard to remember that there is [a professor]."

Student initiative. Student initiative was a common theme, although participants used a variety of terms to describe it. Some talked about self-motivation, "being driven," or being a "self-starter," while others called it "being proactive." Ethan thought a higher level of self-regulation was required of online students. When asked for examples of initiative, students described proactively contacting the instructor. Beth observed, "The student has to be a lot more proactive when it's an online class...especially students who wouldn't typically ask questions in class or really engage with the professor."

Social interaction. The level of interaction varied between courses. Further, the way in which participants described interaction varied. Five students indicated they had no interaction with other students in the online class. However, some of those same students talked about required participation in the class discussion board. When pressed to explain the apparent discrepancy, they did not consider activity on the discussion board the same thing as interaction. Haley characterized it as one-way communication, saying the discussion board is "like someone is speaking, but it's not a conversation." Finally, the perception of value also varied. Upperclassmen and graduate students generally expressed more appreciation for the discussion boards than underclassmen. For example, having taken both undergraduate and graduate courses online, Laura stated, "Online grad courses have been much richer."

Teach yourself. Four interviewees used some variation of the phrase "teach yourself." The phrase appeared to hold multiple meanings. Related to time management and scheduling, Faye said, "Obviously we are the student, but I think when it comes to the online course, we're also the professor because we have to teach ourselves." She described her online course saying, "It was very student-paced and I think that kind of put the student in the professor's position. You taught yourself."

When referring to face-to-face courses, Janet said, "You are getting those academic conversations. You are getting reminders. You might be getting bits of information from other students on things that you missed." She then contrasted that environment to the online situation, saying, "When it's online and you're not meeting regularly and may never meet any of the other students or the instructor, you really have to drive that train yourself."

Chloe commented, "In the online class, you are both the teacher and the student. There's no one there. I mean, you're kind of your own supervisor and there's no one to remind you that you have assignments to do." However, she went on to expand the meaning of being "both the teacher and the student" by saying, "No one's going to be there to really actually explain. You can't go to the classroom and expect the lesson to be gone over that day." She seemed to juxtapose verbal explanation with written explanation, saying, "In an online class, they provide you with the tools and resources to teach yourselves pretty much."

Although they did not use the phrase *teach yourself*, other students also addressed differences between spoken and written communication. Beth compared the content delivery of two different online courses she had taken. “In my pre-calculus class,” she said, “the instructor always had a screencast that she would upload where she would basically teach the lesson as if she was teaching it on a whiteboard...there was voiceover as well.” She then related, “The STAT class didn’t have that, which was kind-of disappointing. He would send out lessons that were summaries of the chapter, essentially, which were a little more difficult to follow than the screencast.” Ingrid commented, “Sometimes you get exhausted from just reading, reading, reading—never hearing someone’s voice and never hearing it summed up in a really nice way.”

Ethan found it more interesting to learn certain subjects on his own and felt online courses were geared for students who liked to “self-teach.” Together with self-paced scheduling and written explanation, students seemed to embed the idea of independent research into the concept of “teaching yourself.”

Comprehensive Results

Having used an explanatory sequential design, all results were analyzed comprehensively at the close of the final phase. These aggregate results revealed significant association between student success and factors that may be categorized as personal, circumstantial, or course variables. For Phases One and Two, variables were intentionally selected based on a theoretical framework that included these categories. Themes emerging from elaborative qualitative analysis in the third phase fell naturally into the framework of personal, circumstantial, and course characteristics.

By design, each successive phase in the explanatory sequential exploration yielded more substantive information. For example, in Phase Two students with higher levels of perceived academic control were shown to earn significantly higher course grades. Expectancy beliefs related to perceived academic control were illustrated in the interviews as students discussed time management, student initiative, and ways in which they “taught themselves” in an online course.

Discussion

The explanatory sequential design provided the foundation for a cohesive and in-depth evaluation of factors related to student success. Quantitative results revealed statistically significant relationships between success in online courses and seven individual factors: three personal variables (cumulative GPA, race, and perceived academic control), two circumstantial variables (class standing and degree level), and two course variables (course level and teaching presence). Cumulative GPA demonstrated the largest effect size among the seven factors. To evaluate combinations of variables and develop predictive models of student success, logistic regression was used and revealed that the variables predictive of success changed with students’ level of academic experience. Interviews with successful students provided deeper insights into their perceptions and experiences. Their comments about personal characteristics and actions coalesced into themes of time management and student initiative, as well as the surprising “teach yourself” theme. Descriptions of their online course experience merged into themes of teaching presence and social interaction. Finally, interviewees discussed the roles of challenges and family support as circumstantial elements pertaining to their success. Although the current study was limited to a single institution, findings may be relevant to inform research at other institutions given the large number of cases and that nearly 10% of cases were students outside the state.

Among prior studies, the personal characteristic of GPA produced more consistent evidence of correlation with student success than any other variable (e.g., Cochran et al., 2014; Hachey, Wladis, & Conway, 2014). The logistic regression analysis in the current study corroborates these findings, supporting the conclusion that students who generally do well academically are more likely to do well in online courses too. Hence, targeted interventions to enhance success in online courses might be directed toward students who are not succeeding overall. While this study focused on successful students, future studies that include unsuccessful students are warranted.

It should be noted that cumulative GPA was captured at the end of the semesters indicated, thereby including the online course being analyzed. Hence, the online course provided a proportionally larger contribution toward cumulative GPA for first-year students compared to seniors. Given the volume of cases and the consistency of findings across all class levels, this issue likely did not impact the conclusions. Further, using the cumulative GPA prior to the semester of analysis would exclude the first semester of first-year students as well as grades in other classes being taken by students during the same semester of analysis.

A statistically significant association between the personal variable of race and success in online courses was revealed, although the effect size was small. More than a quarter of students in the current study declined to disclose their race and were therefore categorized as “unknown race,” likely skewing the conclusions about the relationship between race and success rates and providing no basis for settling discrepant findings in previous research.

Results of the current study indicated a significant relationship between the circumstantial variable of degree level and online course success, again with a small effect size. As might be expected, graduate students achieved the highest success rates in their online courses while non-degree-seeking students had the lowest success rates. Graduate student success could be attributed to their academic longevity or to having focused on a disciplinary area of specific interest and application to their careers. Among undergraduate students, those seeking the lowest level of academic credential (a subassociate occupational endorsement) had the highest online course success rates. Students in this category are typically pursuing workforce development and taking courses immediately applicable to their employment. These results may be indicative of student motivation or may speak to the student’s perception of course relevance. Joo, Lim, and Kim (2013) found that perceived relevance of assigned tasks within a course exerted a significant effect on achievement, and Park and Choi (2009) concluded that perceived course relevance had a significant effect on course completion. One strength of the current study was the unique breadth of degree levels available for inquiry at a single institution. The inclusion of a microcredential such as the occupational endorsement may have strengthened the analyses, allowing for the discrepant conclusion that degree level is a contributing factor of success.

Class Standing and Course Level

Findings in the current study also indicated that class standing, a circumstantial variable, had a significant relationship with success in online courses. Graduate students were shown to have the highest course success rates. Seniors had the second-highest success rates, followed (in descending order) by juniors, sophomores, non-degree-seeking students, first-time freshmen, and continuing freshmen. These results add to evidence of an association between class standing and success, as reported by Cochran et al. (2014) and Levy (2007), indicating that academic experience

progressively scaffolds student success. The finding that first-time freshmen had higher success rates than continuing freshmen is a curious, contradictory result that warrants further exploration.

Results of this study also showed online course level, a course variable, to have a significant, positive relationship with student success, which appears to be a unique contribution to the body of knowledge. Students tend to have more success in courses with higher academic complexity. While this success may be influenced by age, academic experience, and maturity, the link between these factors is not exclusive. Newer students, such as first year and sophomores, sometimes enroll in upper division courses. More frequently, seniors complete a few remaining general education requirements just prior to graduation.

More noteworthy than the simple association between student success and the individual variables of class standing or course level was the discovery that predictive models of combined factors contributing to success differed between various class-standing groups. For example, the combination of variables that predicted success among first-time freshmen differed from variables contributing to success among continuing freshmen. Success is complex, as are the factors that determine it. The current results with supportive evidence in all three phases indicated that factors related to success appear to change with a student's level of academic experience. Interviewing more individuals from each class level in future studies will further enhance the understanding of these interrelationships. Evaluating factors of success across multiple class levels in a single study provided a unique and significant contribution that may help to explain some of the contradictions in previous research. Some previous studies, for example, considered targeted populations, such as community college students (Hachey et al., 2014; Jost et al., 2012) or graduate students (Rakap, 2010; Rockinson-Szapkiw et al., 2016). Other studies evaluated a broad population without examining the predictive factors for a given subpopulation (Levy, 2007; Wang et al., 2013).

Similar to other class modalities, findings of the current study implied that design and delivery of online classes should consider students' current academic level. Online classes designed for sophomores compared to those for seniors therefore need to be different for reasons beyond just the varied level of students' cognitive capacity. Differences in predictive models could also have implications for comprehensive student advising and online student support. Awareness of the factors associated with success at each level of academic experience may empower academic personnel to provide more targeted and effective support.

Evidence that success factors change with academic experience also supports the conclusion that student success is a synergistic relationship between personal, circumstantial, and course variables. As such, these variables are best studied in an ecological fashion rather than in isolation. This conclusion sounds intuitive; theoretical models agree that student success is contextually sensitive and may be influenced by a combination of elements (Bean & Metzner, 1985; Berge & Huang, 2004; Rovai, 2003; Tinto, 1993). Yet relatively few studies have examined objective course outcomes of online students in a comprehensive manner that includes personal, circumstantial, and course variables. If research is to be translated to practice of design, delivery and policy making, it is essential to understand determinants of success at a deeper level than the role of single variables. For example, if an instructor considers only one variable at a time when designing and delivering an online course, the role of that variable and its interrelationship with others is missed.

Perceived Academic Control

The PAC questionnaire, distributed in the second phase of research, assessed students' expectancy beliefs through quantitative analysis of scale scores. The findings suggest that students who believe they have a high level of control over academic outcomes may earn higher course grades. In the third phase of research, qualitative interviews with successful students reflected these expectancy beliefs of PAC as students talked about time management, student initiative, and the need to teach themselves. When asked how they were able to overcome circumstantial challenges and persist to completion, participants spoke of the personal characteristics of determination, self-motivation, hard work, and help-seeking behavior.

These characteristics are congruent with Bandura's (1991) discussion of *locus of control*, which is concerned with whether an individual believes outcomes are determined by their own actions (internal locus of control) or by forces outside their control (external locus of control). Locus of control has been demonstrated as a predictor of academic success in numerous studies related to traditional classrooms (Perry et al., 2001; Stupnisky, Perry, Hall, & Guay, 2012). However, locus of control has shown mixed results among studies of online students. The PAC scale used in this study is domain specific, developed to assess college students' beliefs about academic success (Perry et al., 2001). Current results indicated students with high PAC-scale scores earn higher course grades than students with lower PAC scores. This finding adds to prior evidence that internal locus of control is associated with success in online courses (Lee, Choi, & Kim, 2013; Rogers, 2015).

An important limitation in the current study was the lack of variance among Phase Two respondents. It is unclear whether all successful online students have an equally high level of perceived academic control, or whether internal locus of control prompted this particular set of students to respond to the questionnaire. It would be valuable to extend the study to unsuccessful students, in order to determine whether the variables of perceived academic control and perception of teaching presence differ between successful and unsuccessful students. Likewise, it would be beneficial to expand the number of student interviews to broaden the understanding and generalizability of student perceptions.

Teaching Presence

The current study examined two elements from the CoI process model developed by Garrison and colleagues (2000). Teaching presence was shown to have a statistically significant relationship to final course grade; social presence was not statistically significant. This was confirmed in interviews when students described teaching presence as substantially more important to their success than interaction with other students within the course.

Prior empirical evidence for association between teaching presence and final course grade was scarce. Results of this study revealed final grades to be higher among students who reported high teaching presence than among students who reported lower teaching presence, in agreement with findings by Rockinson-Szapkiw et al. (2016). This finding suggests that success rates in online courses might be improved by increasing practices related to teaching presence.

During interviews, students were asked, "What role did the instructor play in helping you succeed in this course?" Students described several elements of teaching presence, such as responding promptly to emails, providing personal feedback on assignments, providing reminders, and recording lectures as audio or screencasts. Participants discussed the online instructor's role

in contrast to the in-person classroom instructor's role. In face-to-face classrooms, they thought the instructor's role was to lecture and explain, while online, the instructor's role was to guide and provide resources. This description of instructor roles did not necessarily reflect student ideals but was a description of their lived experience. It followed that several participants said the online student role was, in part, to teach oneself.

Teach Yourself

"Teach yourself" was, in fact, one of the most interesting and surprising themes to emerge from the interviews. Student statements related to teaching themselves seemed puzzling at first, given that the same students reported online instructors to be instrumental to their learning. Three elements of "teach yourself" emerged in their descriptions. First, online students are responsible for their own schedules and effort regulation, to a much greater degree than what is expected of students in classroom courses. Second, online course material is often delivered in written form, while in-class lectures are usually delivered verbally. Some students seemed to equate teaching with oral presentation. These students implied that written presentation necessitated "self-teaching." Finally, students indicated that online courses required more independent research than in-person courses.

When an instructor delivered lecture material in written form, or explained something using text rather than speech, students tended to call the activity *guidance* rather than *teaching*. This dichotomy raises interesting questions. It might be construed that reading, by its very nature, is a more active endeavor than listening. However, it is also plausible that students have been conditioned through past educational experience to equate teaching with verbal presentation. Rogers (2015) argued that students have come to expect a lecture format because that is what they have traditionally experienced. As students move from high school to college, they are expected to become more responsible and self-directed (Wadsworth, Husman, Duggan, & Pennington, 2007). Nevertheless, unanswered questions about student perceptions of reading versus listening provide an opportunity for further research. This question might be explored by comparing groups of students with various educational backgrounds. For example, perceptions of students who completed high school via homeschooling might be compared to perceptions of students who graduated from public or private high schools.

Researchers who developed the CoI model, which encompasses teaching presence and social presence, called text-based communication a "lean medium," acknowledging that it lacked the richness of verbal communication. On the other hand, they believed it might be advantageous for rigorous cognitive learning because it slows interaction time and allows opportunity for reflection (Garrison et al., 2000). Graduate students in the current study seemed to support that notion, expressing appreciation for the egalitarian nature of online discussions with peers. By contrast, the underclassmen who were interviewed found discussion board participation less meaningful. Post hoc evaluation of social presence scale scores among the 12 interviewees confirmed that graduate students rated social presence higher than undergraduates, although the sample size is certainly too small to draw conclusions. Interestingly, the CoI model was originally developed through research on graduate-level courses.

Conclusion

An explanatory sequential research design in the present study afforded deeper understanding of the factors related to online student success, perhaps addressing some of the contradictions in previous studies. The current mixed methods design was a useful reciprocal tool since qualitative results augmented quantitative results, and the latter confirmed the accuracy of interviewees' comments. Students who were successful in online courses offered a valuable perspective about what contributes to their success—a piece that is often missing when administrators and faculty try to improve online experiences. This strengths-based approach was a key to understanding factors of success, providing opportunities for inclusion strategies that can complement existing deficit-based exclusion strategies when designing and delivering online courses. While the term *success* can be operationalized in so many ways, it remains context-sensitive and multifaceted, thereby necessitating more complex investigative approaches to understanding underlying factors.

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Appendix A

Phase Two Questions

1. During Spring 2015 semester, what was your work situation?
 - a. I was working full time
 - b. I was working part time
 - c. I did not have a job
2. Did either of your parents graduate from college?
 - a. yes
 - b. no
3. During Spring 2015 semester, did you spend significant time and effort caring for others in your family, such as children, siblings, or elders?
 - a. yes
 - b. no

Please mark the level to which you agree or disagree with each of the following statements. (1, strongly disagree; 5, strongly agree)

4. My grades are basically determined by things beyond my control and there is little I can do to change that. (Reverse scoring.)
5. My family is willing to help me make decisions.
6. Your intelligence is something about you that you can't change very much. (Reverse scoring.)
7. I have a great deal of control over my academic performance in my online courses.
8. No matter what academic challenge comes my way, I'm usually able to handle it.
9. If I am in a bind in my courses, I can usually think of something to do.
10. I can count on my friends when things go wrong.
11. My friends really try to help me.
12. I can solve most academic problems if I invest the necessary effort.
13. I see myself as largely responsible for my performance throughout my college career.
14. When I encounter an academic obstacle, I can find a way to overcome it.
15. Thanks to my resourcefulness, I know how to handle unforeseen situations in my academic career.
16. I can talk about my problems with my friends.
17. You can always substantially change how intelligent you are.
18. My family really tries to help me.
19. There is little I can do about my college performance. (Reverse scoring.)
20. There is a special person with whom I can share my joys and sorrows.
21. I can always manage to solve difficult academic problems if I try hard enough.
22. The more effort I put into my courses, the better I do in them.
23. I can talk about my problems with my family.
24. It is easy for me to stick to my aims and accomplish my academic goals.
25. No matter who you are, you can significantly change your intelligence level.
26. You can learn new things, but you can't really change your basic intelligence. (Reverse scoring.)

27. How well I do in my courses is often the “luck of the draw.” (Reverse scoring.)
28. No matter what I do, I can’t seem to do well in my courses. (Reverse scoring.)
29. No matter how much intelligence you have, you can always change it quite a bit.
30. When I do poorly in a course, it’s usually because I haven’t given it my best effort.
31. I have friends with whom I can share my joys and sorrows.
32. I have a special person who is a real source of comfort to me.
33. To be honest, you can’t really change how intelligent you are. (Reverse scoring.)
34. You have a certain amount of intelligence, and you can’t really do much to change it. (Reverse scoring.)
35. I can remain calm when facing academic difficulties because I can rely on my coping abilities.
36. I get the emotional help and support I need from my family.
37. There is a special person in my life who cares about my feelings.
38. You can change even your basic intelligence level considerably.
39. There is a special person who is around when I am in need.
40. When I am confronted with an academic problem, I can usually find several solutions.
41. I am confident that I can deal efficiently with unexpected academic challenges.

The email inviting you to participate in this research study referred to a specific online course. Please mark the level to which you agree with each of the following statements related to that specific course. (1, strongly disagree; 5, strongly agree)

42. Instructor actions reinforced the development of a sense of community among course participants.
43. I felt that my point of view was acknowledged by other course participants.
44. I felt comfortable disagreeing with other course participants while still maintaining a sense of trust.
45. The instructor provided clear instructions on how to participate in course learning activities.
46. The instructor helped to focus discussion on relevant issues in a way that helped me to learn.
47. Online or web-based communication is an excellent medium for social interaction.
48. The instructor clearly communicated important course topics.
49. Online discussions help me to develop a sense of collaboration.
50. The instructor was helpful in guiding the class towards understanding course topics in a way that helped me clarify my thinking.
51. I felt comfortable participating in the course discussions.
52. I felt comfortable interacting with other course participants.
53. The instructor helped to keep the course participants on task in a way that helped me to learn.
54. The instructor helped to keep course participants engaged and participating in productive dialog.
55. The instructor provided feedback in a timely fashion.
56. The instructor provided feedback that helped me understand my strengths and weaknesses relative to the course’s goals and objectives.
57. I was able to form distinct impressions of some course participants.

58. Getting to know other course participants gave me a sense of belonging in the course.
59. The instructor clearly communicated important course goals.
60. The instructor encouraged course participants to explore new concepts in this course.
61. The instructor clearly communicated important due dates/time frames for learning activities.
62. The instructor was helpful in identifying areas of agreement and disagreement on course topics that helped me to learn.
63. I felt comfortable conversing through the online medium.

Student Perceptions of the Most Effective and Engaging Online Learning Activities in a Blended Graduate Seminar

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Abstract

The principal concern of this research was to learn more about effective designs of learning activities in online environments. A questionnaire was administered in three sections of a not-for-credit intensive blended graduate seminar in university teaching. The online activities included readings, videos, discussion forum activities and other activities using a range of web-based technologies. Students rated each of the activities on four target criteria: alignment with the course learning outcomes, deep learning, engagement, and value. Students also were asked to identify the most useful activities for each of the five modules and evaluate the course as a whole in terms of navigation, expectations, instructions, availability of materials, instructor presence, and technical quality of media. The results suggest that students' perceptions of the activities followed very similar patterns across the four target criteria. The discussion highlights four distinct design features that characterize the most highly rated activities.

Keywords: online engagement, student engagement, higher education, blended learning, hybrid learning

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Student Perceptions of the Most Effective and Engaging Online Learning Activities in a Blended Graduate Seminar

In online and blended learning environments, a key determinant of effectiveness is the ability of the online environment to engage the learner. The nature of online learning activities varies greatly, ranging from information transfer (e.g., videos and readings) to active, collaborative assignments. Although there is an abundance of research on the factors (e.g., cognitive, social presence) that contribute to the effective design of an online course as a whole, research on the nature and design of specifically the online elements is scant. The purpose of this study is to

examine the nature of online learning activities that students find engaging and helpful in achieving their learning outcomes.

Review of Related Literature

Most of the literature to date on the design of and engagement in online environments has generally focused on frameworks, strategies, and instructional planning for courses as a whole and not on the design of individual learning activities within a broader context (Moore, 1989; Martin & Bolliger, 2018; Garrison & Vaughn, 2008; Graham, Cagiltay, Lim, Craner, & Duffy, 2001; Helms, 2014). Careful big-picture thought and planning is essential to the development of any course, but it is also imperative to consider the role and design of individual activities as they relate to the overall objectives of a course. Below is an introduction to the relevant literature.

Redmond, Abawi, Brown, and Henderson (2018) propose a framework for engagement as a tool for facilitating and evaluating online and student engagement at the course and program level. This framework was based on earlier foundations of engagement that centered around behavioural, emotional, and cognitive dimensions (Fredericks, Blumenfeld, & Paris, 2004). The Online Engagement Framework for Higher Education consists of the five following interrelated elements: social engagement, cognitive engagement, behavioral engagement, collaborative engagement, and emotional engagement. The authors suggested that instructional designers use the framework to “raise awareness and build capacity” (p. 197) as they relate to the elements.

Garrison, Anderson, and Archer’s (2000) Community of Inquiry (CoI) is a widely used and adapted framework for promoting engagement and collaboration in online environments (Garrison et al., 2009) but has been widely associated with blended learning. The framework consists of three overlapping elements critical to teaching and learning in an online environment in higher education: teacher presence, social presence, and cognitive presence (Garrison et al., 2009). Central to this framework is the role of the teacher, who designs and facilitates the online experience in a way that promotes the other two facets—cognitive and social presence. The idea that it is indeed the instructor that designs, scaffolds and facilitates the students’ cognitive and social presence is key in the planning of any online environment. While a key aspect of teacher presence is to facilitate and be present during the learning process, it is the deliberate design of a course and its activities that provides students with the opportunities to think critically and collaborate with each other.

One of the most well-established starting points for discussions about online learning activities is Moore’s (1989) three types of interaction. These are learner-content interaction, learner-instructor interaction, and learner-learner interaction. Moore stressed the importance of including all three types of interaction in any type of distance course, regardless of the medium or media used. At the time, he acknowledged the challenge in implementing the third type into both thinking and practice. Rapid development of digital tools and the widespread adoption of LMSs into higher education has made learner-learner interaction easier to design, but learner-content interaction—namely in the form of video lecture and readings—often still outweighs learner-learner (and sometimes learner-instructor) interaction (Boling et al., 2012). Martin and Bolliger’s (2018) research into the perceptions of activities and strategies as they relate to each of Moore’s types of interaction confirmed that all three types are highly valued by students and promote engagement. The learner-instructor engagement indicators received the highest ratings of the three types.

As higher education pedagogies slowly shift from a teaching focus to a learning focus, the question becomes, how do we transform the learner-learner, learner-content, and learner-instructor relationships to promote this philosophy? As the role of the instructor changes and, therefore, the nature of learner-instructor interaction, how can we design individual learning activities within a course system that change the way students interact with content? The need for this understanding is particularly relevant as more courses and programs are shifting to blended and fully online formats.

The principal concern with this research is to learn more about how best to design individual learning activities within an online environment that are effective and engaging.

Methods

Research Questions

The following research questions guided this study:

- Which kinds of online activities do students perceive as more/less effective in helping students achieve learning objectives?
- Which kinds of online activities do students perceive as more/less engaging?

Context

The Graduate Seminar in University Teaching (GSUT) is a long-running, 35-hour course offered by the Centre for Teaching and Learning to graduate students. The purpose of the seminar is to prepare graduate students for an academic teaching career. It is typically delivered as an intensive course with five full days of instruction either over one week or once per week over five weeks. While some sections of the course are discipline specific (i.e., fine arts, engineering), the blended section is open to students from all disciplines.

In 2016, the GSUT was offered as a blended course for the first time by reducing the number of hours spent in class each day from seven to four in order to make the learning experience more flexible for participants and reduce the intensity. As a result, three and half hours of course activities were moved out of in-class sessions to online using the university's learning management system (LMS), Moodle, in conjunction with other web tools.

As the planning for the development of the course began, questions about online activity development emerged: Which kinds of activities are most engaging? Which kinds activities are most useful to students in meeting the course goals and outcomes?

The blended version of the course was developed using Wiggins and McTighe's (2001) backward design process. The learning outcomes and assessments remained the same as in other sections of the course, but the task was to identify activities that would promote student learning aligned with the course learning outcomes. For each learning outcome, a set of instructional activities was devised: those best suited for in-class and those best suited for the online environment were identified and developed.

Some online activities were extensions of in-class activities or topics while other topics were addressed exclusively online. In some cases, the decision to put activities online was related to the order in which they should be introduced to students. Table 1 provides an overview of all the online activities and their associated characteristics.

The online activities included some direct instruction, such as readings (either scholarly or more practical in nature), videos (interactive or not), and websites. Every effort was made to make the course as interactive as possible. For example, one set of YouTube videos was made interactive using a tool called EdPuzzle. Learner-learner interaction was also prioritized by developing several collaborative activities. These were facilitated through the use of discussion forums and a Google Doc. The flexibility of the discussion forum as a mechanism allows for a lot of variation in the design of the kinds of tasks students can perform. To take advantage of this flexibility, several types of learning activities were designed; these included structured peer review of assignments, collaborative content creation, debate, and reflection.

Table 1
Characteristics of Course Online Activities

Activity Name	Activity Type	Interaction Type(s)	Level of Thinking
Forum: Peer Review Assessment Plan	Peer review	Learner-learner Learner-content	Evaluate Create
Forum: Peer Review TPS	Peer review	Learner-learner Learner-content	Evaluate Create
Forum: Share a Course Policy	Share content	Learner-learner Learner-content Learner-instructor	Evaluate Create
Forum: Issues in Assessment	Defend a position	Learner-learner Learner-content Learner-instructor	Evaluate
Video: Rubrics	Direct instruction	Learner-content	No output
Forum: Video & Discussion - Seven Principles	Collaborative task	Learner-learner Learner-content	Understand Apply
Explore UDL Website	Direct instruction	Learner-content	No output
Reading: Lesson Planning	Direct instruction	Learner-content	No output
Interactive Video: Teaching Teaching & Understanding Understanding	Direct instruction	Learner-content	Understand
Forum: Issues in Teaching	Problem-solving scenarios	Learner-learner Learner-content Learner-instructor	Evaluate Create
Forum: Share a Syllabus	Content-sharing	Learner-learner Learner-content	Evaluate
Quiz: UDL	Check understanding	Learner-content	Understand Apply
Reading: Deep & Surface learning	Direct instruction	Learner-content	No output
Forum: Reading & Discussion on Conditions of Assessment	Direct instruction & reflection	Learner-learner Learner-content Learner-instructor	Apply
Reading: Ten Tips for Grading	Direct instruction	Learner-content	No output
Reading: Learning Principles	Direct instruction	Learner-content	No output

The student questionnaire was administered in three sections of the seminar taught by the same instructor, which ran in spring and fall of 2017, and winter 2018. In total, 59 students (spring $n = 19$; fall $n = 12$; winter $n = 28$) across all three sections responded to the questionnaire out of 74 students who completed the course, making the response rate 79.72%. An invitation to participate in the research was sent in advance via an announcement in the course LMS with all the relevant information. A paper-based student questionnaire was administered by a member of the Centre's staff on the last day of the course along with the usual course evaluation. Participation was completely voluntary, and no compensation was provided for those who participated. All responses were anonymous.

All but five of the respondents of the questionnaire were master's ($n = 29$) or PhD ($n = 25$) students. There was one undergraduate student and four "other," which were certificate or diploma students.

The questionnaire was divided into three sections. The first section asked students for information about their studies, motivations for taking the seminar, motivations for taking the blended section of the course, and general preferences about online learning. It also included some questions that asked them to rate the amount and quality of their interactions with the instructor and their peers, as well as opportunities for learning, reflection, and feedback.

The second part of the questionnaire focused on asking students four questions about their perceptions of online activities completed in the course, organized by module. In total, respondents were asked to rate 19 online activities in terms of how much they agreed with the following statements: (1) This activity helped me achieve the learning outcome; (2) this activity helped me achieve deeper learning on the topic; (3) this activity was engaging; and (4) this activity was a valuable part of the course overall. Response to each statement was presented as a five-point scale ranging from 1 (*disagree*) to 5 (*agree*), with 3 as *no opinion*. The participants were also optionally able to provide comments on each of the activities. These rating items were supplemented by open-ended items asking participants which activities were the most and least useful, and how the activities could be improved. Because of adjustments to the course syllabus, in certain sections one or two activities were replaced with face-to-face activities. These activities received fewer ratings overall.

The third section of the questionnaire focused on the online portion of the course as a whole. In this section, participants evaluated the course in terms of ease of navigation, clarity of expectations and instructions, availability of materials, instructor presence, and technical quality of media. Students were also asked to share their biggest challenge in completing the online activities.

The first and third sections of the questionnaire included or adapted questions from Garrison and Vaughn's (2008) *Student Survey Questionnaire*. The questionnaire was reviewed by two staff members at the Centre for Teaching and Learning, who were instructional designers with expertise in educational technologies.

The questionnaires were collected and transcribed for analysis. Descriptive statistics (percentages, median, range) were used to analyze the quantitative ratings, and thematic analysis was used to analyze the students' written comments. Based on a preliminary review of the data, students' ratings of three of the online activities were excluded from the final results. In two cases, answers to the open-ended items about the activity suggested that the respondents had confused

the online activity with a related in-class activity. In the third case, too few students had responded to the question.

Limitations

Some methodological limitations need to be mentioned. The sample was a group of graduate students who were drawn from a section of a seminar offered by one instructor at a single institution. Only one section of the course was being offered in a blended format at the time of the study. Additionally, this study is limited to perceptions of usefulness and engagement, but other types of outcomes should also inform the design of design of blended courses, such as learning outcomes and attitudinal changes, and conceptual changes in approaches to teaching.

Results

Respondents ($n = 59$) from three sections at least partially completed the questionnaire. Some students had not yet completed all the online activities on the last day of class when the survey was administered and were, therefore, unable to rate certain activities. In addition, three of the activities were not used in all sections of the course. Therefore, not all activities were rated by all 59 respondents. Table 3 indicates the number of respondents for each activity.

Student Motivations and Learning Preferences

Twenty-four (40.68%) respondents reported that they had not known they had registered for a blended section of the seminar. Table 2 shows the reasons respondents chose the blended section of the seminar. They were able to select more than one reason. The two “Other” reasons respondents listed were that it was the only section open at the time of registration ($n = 3$), and they wanted to experience a blended course ($n = 2$).

Table 2
Reasons for Choosing a Blended Learning Course

Reason	<i>n</i>
I like the flexibility of completing assignments anytime/any place	19
It was the only available option that fit my schedule	9
Other responsibilities make it difficult for me to attend an all-day course	12
Other	5

Note. Number of respondents = 35. Some respondents reported more than one reason.

When asked what balance of online versus in-class activities they prefer, more than half (55.9%) of respondents reported preferring an equal mix of face-to-face and online activities, while about a third (32.2%) preferred mostly face-to-face activities. Entirely online and entirely face-to-face were rated the least preferred modalities at 3.4% each, while only three of the respondents (5.1%) preferred mostly online.

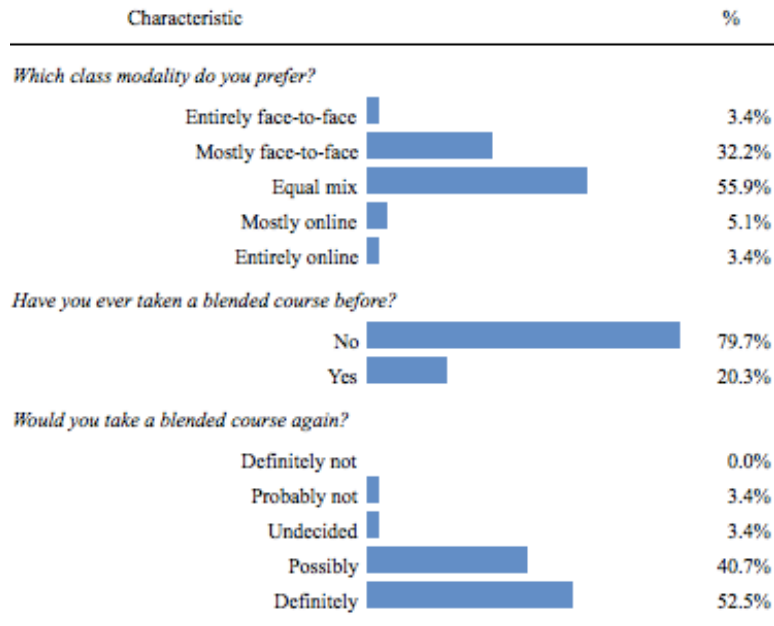


Figure 1. Student characteristics as a percentage of the sample. Note. N = 59.

Nearly 80% (79.7%) of respondents had never taken a blended course before. When asked if they would take a blended course again, over half reported they definitely would, while over 40 percent (40.7%) said they possibly would. Only 3.4% said they probably would not, while another 3.4% reported being undecided. None of the respondents had completely ruled out taking another blended course.

Perceptions of Activity Quality

Overall perceived quality. Ratings for the course activities were typically high, with positively skewed distributions.

Each activity received a separate rating for its (1) alignment with the course learning outcomes, (2) ability to promote deep learning, (3) engagement, and (4) perceived value. These ratings were summed to create a scale indicating an activity’s overall quality. Cronbach’s alpha for each activity’s scale ranged from .86 to .97, indicating high internal consistency. Median scale scores for each of the 19 online activities are summarized in Table 3.

Using this summed score as an overall indicator, nearly half ($n = 8$) of the 17 activities received a score of 16 out of a possible 20. These included online readings, videos, and other online activities.

The four highest rated activities were all discussion forums used in a few different ways. The two highest rated activities overall were both peer review activities facilitated in a discussion forum. The third- and fourth-highest-rated activities were also discussion forums but made use of the forum in different ways. These were the Share a Course Policy and the Issues in Assessment forums.

Table 3
Median Ratings for Perceived Overall Quality

Activity	Median	<i>n</i>
Forum: Peer Review Assessment Plan	20	56
Forum: Peer Review TPS	18.5	56
Forum: Share a Course Policy*	18.5	38
Forum: Issues in Assessment	17	57
Video: Rubrics	16	56
Forum: Video & Discussion - Seven Principles	16	57
Explore UDL Website	16	53
Reading: Lesson Planning	16	55
Interactive Video: Teaching Teaching & Understanding Understanding	16	57
Forum: Issues in Teaching	16	54
Forum: Share a Syllabus	16	56
Quiz: UDL	15.5	50
Reading: Deep & Surface Learning	15	56
Forum: Reading & Discussion on Conditions of Assessment	15	56
Reading: Ten Tips for Grading*	14	26
Reading: Learning Principles*	14	39

Note. Activities marked with “*” were only used in two of the three course sections.

There were five activities that received an overall median score of less than 16. The bottom two activities were both short online readings from academic sites aimed at faculty. The third- and fourth-lowest-rated activities were more academic in nature. One was a forum activity that required students to read a journal article available for free online on the topic of assessment and reflect on the reading afterwards. The other reading was a digital copy of 10 pages from a book, which students accessed via the LMS, provided by the library. The only online quiz also scored in the bottom five.

Activities by perceived engagement rating. Nine of the 17 activities received a median score of four for engagement. Of those which scored higher than 4, three received a median rating of 5 (out of 5) and one received a score of 4.5. In each case, at least half of respondents agreed each of the activities was engaging and none disagreed that they were engaging. Although the order is slightly different, the most engaging activities correspond with the highest rated activities overall.

The Peer Review of Assessment forum was rated the most engaging, with nearly two thirds (63%) of respondents agreeing and 21% somewhat agreeing that it was engaging. The second-most-engaging activity was the Issues in Assessment forum, with more than half (54%) agreeing and about a quarter (28%) somewhat agreeing, while the Peer Review TPS came in third-most-engaging, with about half (52%) who agreed and a quarter (25%) who somewhat agreed it was engaging. The Share a Policy forum received a median score of 4.5, and half (50%) of respondents agreed and 26% somewhat agreed that the activity was engaging.

The four activities that received median scores below 4 were all readings, though one was a reading that required students to respond in a forum. This Reading and Discussion on Assessment forum received a median score of 3.5, with the majority of respondents having no opinion about how engaging it was.

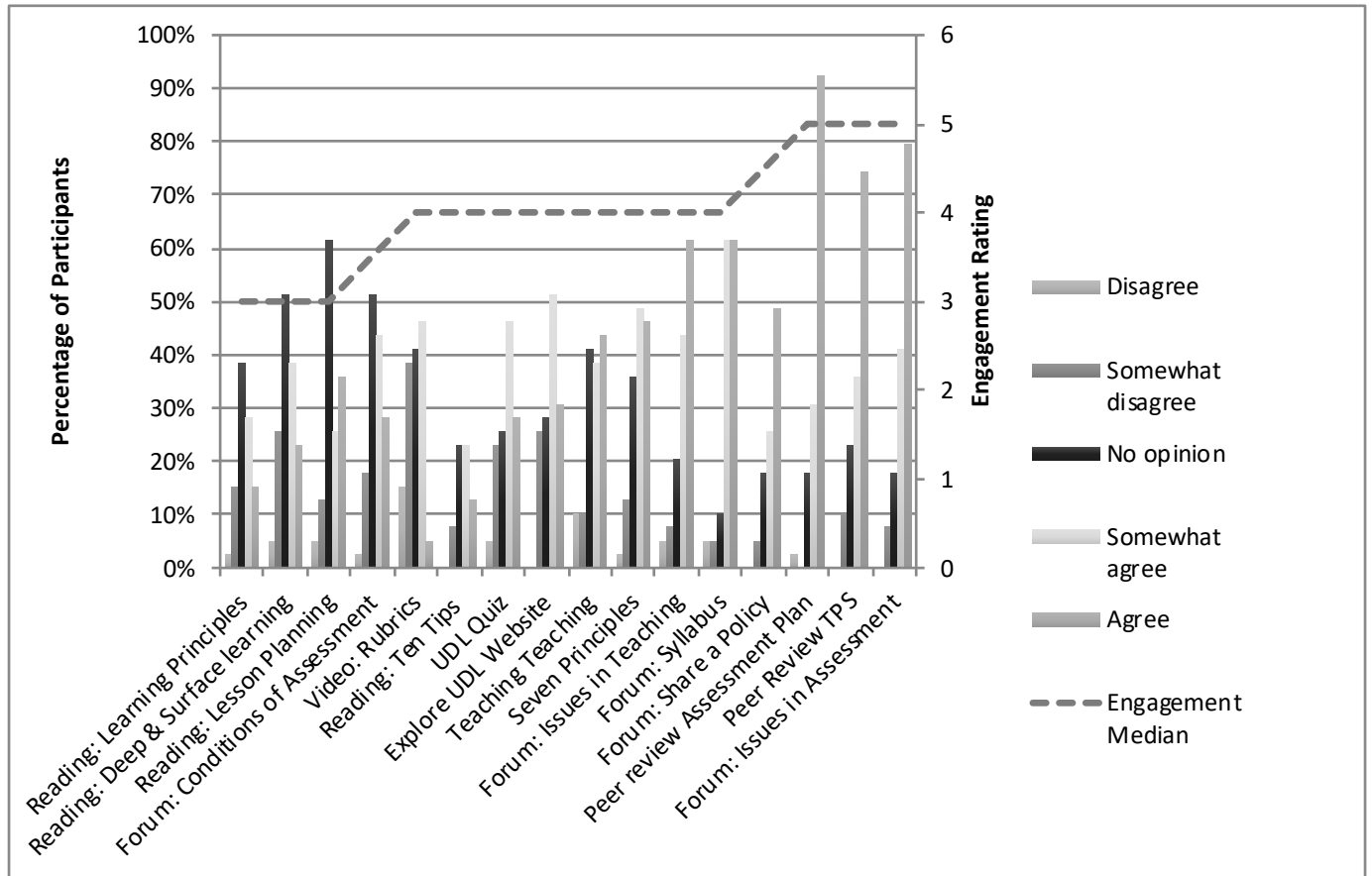


Figure 2. “This activity was engaging” question ratings and median.

The remaining three lowest rated activities each received a median score of 3. All were online readings from academic websites, and the largest numbers of respondents didn’t have an opinion on engagement related to each of them.

Discussion

Student Motivations and Learning Preferences

The purpose of asking what balance of online versus face-to-face respondents preferred was to determine what might be a good balance in the planning of blended courses. Results were clear that an equal mix of both was ideal for more than half of all respondents, and very few respondents reported preferring learning completely online or face-to-face. Blended courses offer the flexibility to students that traditional face-to-face courses do not without completely sacrificing the face-to-face component. Osgerby’s (2013) research in undergraduate courses also showed that students valued the face-to-face and considered it to be extremely important in the instruction of difficult concepts component, but they appreciated the use of an LMS for certain types of activities.

As the results about respondents’ motivations for enrolling in a blended section of this course show, students were drawn to the flexibility of being able to complete course work at any

time anywhere and being able to make it fit into their schedules. Crews and Butterfield (2014) found similar results in a study of flipped learning where 43% of students rated structure the best characteristics of the online classes, with most comments relating to scheduling, flexibility, organization, and expectations.

From these findings, we can suggest two implications moving forward. As the majority of respondents reported preferring an equal mix of online and face-to-face learning, this could be used as a guideline in the planning of future blended courses. Although *equal mix* was not defined in the survey, the authors assumed the respondents would recognize this as an approximate 50-50 division of the course between online and face-to-face instruction. Secondly, this same finding suggests that a blended format might be favourable to completely online courses or face-to-face courses. Considering more than half of respondents said they would definitely take a blended course again, adding more blended course offerings might be an opportunity to suit students' needs while also helping to reduce the strain on resources within institutions by allowing two courses to be scheduled in the same room, sharing the same time slot.

Perceptions of Quality

The principle concern of the research was to inform online activity design. From the results of the individual activities, four of the 17 activities stand out positively from the others in all areas: alignment with outcomes, deep learning, engagement, and overall value.

Highest rated activities. In particular, two of these stand out for earning perfect median scores of 5 in all four questions. Both of these activities were peer review activities facilitated through the use of discussion forums.

Peer Review Assessment Plan. As part of the course requirements, students had to develop a syllabus that they submit at the end of the seminar for a course they are teaching or would like to teach. The seminar's structure guided students through the three steps of Wiggins and McTighe's (2001) backward design. Through in-class and online activities, students devised both course learning outcomes and an assessment plan for their course.

This peer review activity was designed to help students get feedback from their peers on the first steps of this final syllabus assignment. Students posted their learning outcomes and assessment plans into a group forum where they gave feedback to and received feedback from at least one other student. The instructor provided specific prompts in the forum instructions about what to look for when providing feedback.

Peer Review TPS. One of the other assignments in the course was for students to write their own Teaching Philosophy Statement (TPS). After participating in in-class discussions about the assignment, viewing samples, and completing a reading, students wrote a first draft. The instructor created group forums where students of the same group could upload and view each other's drafts. Each student was responsible for providing feedback to two other group members (determined in class on the first day). The instructor provided a template in the forum with specific prompts as a guide for giving feedback. Students uploaded their statements as attachments to the forum by a certain date and had between five and seven days to reply to those had been assigned to them.

Share a Course Policy. This forum was designed to get students discussing important and often contentious issues in the classroom while also providing scaffolding for their final assignment. Students were asked to devise a course policy for their syllabus assignment and share it with the entire class. The instructor suggested possible themes, but students were permitted to

write policies on whatever they wanted. They were also encouraged to give permission to their peers to use the posted policies as a way of co-creating content.

Issues in Assessment. This forum was designed as a debate around contentious issues on the topic of assessment. The instructor prepopulated the forum with eight to 10 threads that contained the contentious statements in the subject line. Students were instructed to choose one that they agreed with and one that they disagreed with and reply to the thread, defending their opinions for each. The instructor monitored the discussion forum and would typically post replies under each of the statements after two or three students had posted an opinion and then again the day after the due date.

The activities that were rated as most engaging and had the highest overall summed scores were all activities that required students to collaborate or share insights with each other. These all used discussion forums as the mechanism for the activities. However, use of a discussion forum does not necessarily make an activity engaging, as less favourable ratings for forums in this course show. Discussion forums are not inherently effective or engaging in themselves, as they are simply mechanisms. However, the fact that a discussion forum is one of the few ways to facilitate learner-learner interaction (and all three types of interaction at once, in fact) in most LMSs is relevant. What makes the forum more or less effective is the design. So the question becomes this: What makes the activity effective and engaging?

Commonalities of highest ranked activities. It is worth noting that the highest ranked activities included indicators from all three elements of Garrison, Anderson, and Archer's (2000) CoI and most—if not all—of Redmond et al.'s (2018) online engagement elements: social, cognitive, behavioral, collaborative, and emotional engagement. However, if we examine the design and requirements of these activities closely, four particular design characteristics are common among all four: They all (a) promote higher order thinking skills at either one or both of the highest levels of Bloom's revised taxonomy (Anderson & Krathwohl, 2001); (b) promote learner-learner interaction and learner-content interaction; (c) provide feedback on ideas or work; and (d) provide personalization of content or task in one way or another. Each of these four design characteristics is discussed in more detail below.

Promotion of higher order thinking skills. At institutions of higher learning, it is expected that students graduating will be critical thinkers, but this expectation is in conflict with the traditional models of instruction. Participants in Boling et al.'s (2012) research interviews confirm that traditional approaches in online courses have included a lot of reading, rarely followed up with any kind of activities to help students make connections or that promote higher level thinking. In order to promote these skills, instructors need to explicitly scaffold them and provide opportunities for students to practice.

Redmond et al. (2018) point to several indicators of the cognitive engagement element of their framework, such as thinking critically, integrating ideas, and justifying decisions, to name only a few. It stands to reason that in order to elicit these kinds of behaviors from students, tasks must be designed in such a way as to scaffold and prompt students to elicit the specific outcomes desired. If the ultimate goal is to get students thinking and acting like disciplinary experts, what kinds of tasks will help them?

Promotion of learner-learner interaction. One participant succinctly made the following point about the most effective part of the course as a whole: “The fact that it is Blended [underlined]. We had the opportunity to learn from the teacher, classmates and later go back home

and read & interact.” The point here is that the learning does not stop once a student leaves the classroom, and in the case of a blended course with opportunities for learner-learner interaction, students are not completing homework activities in isolation, but rather continuing to build dialogue that deepens understanding and promotes reflection. Participants in Martin and Bolliger’s (2018) research singled out small group discussions in particular as important to encourage reflection and promote understanding in the online environment.

One respondent pointed to another benefit by revealing they “got the chance to interact [with] most peers whom otherwise I would not in a face-to-face only environment.” Blended courses offer a unique opportunity for students to interact with those they do not necessarily have contact with in the usual classroom setting. This is particularly relevant in large classes, where few opportunities for learner-learner interaction exist in the typical class. Northey et al. (2015) found that students reported higher engagement and final grades against a control group when they used a Facebook page to supplement a large lecture class. Additionally, research [as cited in Paskey, 2001] from Athabasca University’s online programs suggests that online discussions between students could potentially outnumber the interactions students might typically have in a usual face-to-face classroom and, therefore, be more involved in learning.

It is important to note that learner-instructor interaction was not common in all the top-ranked activities, which contradicts Martin and Bolliger’s (2018) findings. That is not to say the role of the instructor is not important, but it is worth pointing out that the most highly ranked learner-instructor indicators of their study could be classified as logistical or administrative. However, despite the absence of explicit learner-instructor interaction, there was still what Garrison, Anderson, and Archer (2000) categorize as *teacher presence*. Instructional management is a category of teacher presence, which includes such tasks as initiating the discussion and setting up groups. Therefore, teacher presence was valued more than teacher interaction.

Provision of feedback on their contributions. Three of the four most highly rated activities gave students the opportunity to share the whole or parts of an assignment before submitting it to the instructor. Two of these were explicitly designed as peer review activities where students had to provide feedback to one or two of their group members depending on the activity. In two of these activities, there was little to no instructor-learner interaction by design. In Topping’s (1998) review of the literature, “peer assessment appears capable of yielding outcomes at least as good as teacher assessment and sometimes better” (p. 262). The purpose of these activities was for students to evaluate other students’ work based on the principles learned in class to deepen their own understanding and receive helpful feedback before submitting the assignment formally to the instructor. That is, this was an assessment *for* learning rather than an assessment *of* learning.

Mulder et al.’s (2014) research on student perceptions of peer review through a pre-activity and post-activity peer review questionnaire found that students’ perceptions of its usefulness were positive despite dropping slightly, most notably in a first-year course, after completing the activity. However, there was no change in their perception of the competence of their peers in providing feedback, as only a small number reported concerns about the quality of their peers’ comments; however, one of the concerns students commonly identified was not being able to match the quality of review of that they received. One of the main findings was that students’ opinions about the usefulness of writing reviews of other students improved after completing the activity.

Provide personalization of content or task. All of the top-ranked activities in this study offered some form of personalization, whether it was in the form of individualized feedback in the

peer review activities, or as an element of choice in the task. This desire for customization is confirmed in Ausburn's (2004) research on perceptions of online design elements in a blended course, which found that respondents overwhelmingly ranked *Provide options for individualization/customization of learning* as the most important instructional goal from a list of 15. In her discussion of the data, she draws parallels between the phenomenon of mass customization in an information society and the expectations of students wanting the same personalized experience in higher education, and she encourages faculty and instructional designers to take note.

The concept of choice or options is not exclusive to task-based learning activities. The emerging literature on inclusive teaching practices and Universal Design for Learning (UDL) promotes the idea of providing students with choice in delivery of content and the ways in which they might demonstrate their learning (CAST, 2018). CAST (2018) suggests using multiple means of representing content, which means making it available in different formats (i.e., video versus reading). However, allowing students a choice in the content itself, such as a choice among a selection of readings on the same topic (perhaps from different perspectives), can also serve as important individualization. Participants in Martin and Bolliger's (2018) reported placing a high value on both these notions of choice.

Lowest rated activities. The activities that rated lowest both overall and in terms of engagement were readings, both scholarly and nonscholarly, and one quiz. These were all activities that were exclusively learner-content activities (except for one), and the majority of these did not require any kind of output on the part of the student. The readings, in general, were not immediately followed up by a task, and without an output on the part of the student, the purpose and depth to which they should engage might have been unclear. In other words, there was no cognitive or behavioral engagement or any of the other elements identified in Redmond et al.'s (2018) framework for online engagement. Although one reading did ask students to reflect on their biggest take away in a whole-class discussion forum, this focus on understanding (as opposed to the higher levels in Bloom's taxonomy) may not have been sufficiently cognitively engaging. This may also apply to the only quiz of the course, which emphasized only lower level understanding.

Conclusions

The following conclusions may serve as guidelines to those designing online learning experiences, such as faculty, educational developers, instructional designers, educational technologists, and IT staff who are in decision-making positions with regard to the selection and implementation of learning technologies.

These results suggest that passive online activities, such as videos and readings, are not as effective as well-structured activities that have students collaborating with or learning from other students. However, that is not to say that there is no place for readings or videos in an online environment, but perhaps more thought can be put into how to integrate the readings into other course activities or provide more customization of content to engage students emotionally.

The high scores for these peer-review-type activities suggest that students benefit from seeing and analyzing the work of others and that reviewing each other's understanding, ideas, and writing is a worthwhile exercise. While discussion forums are one way to facilitate peer review

activities, more robust and specialized tools exist and should be explored in order to better facilitate these kinds of activities.

Above all, the design of online activities should prioritize learner-learner interaction in ways that promote thinking at the highest levels of Bloom's taxonomy through social, collaborative, cognitive, and behavioral engagement.

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Effective Tagging Practices for Online Learning Environments: An Exploratory Study of Approach and Accuracy

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Abstract

This exploratory study examines student tagging activity within a five-week social bookmarking unit. Students in six sections of a course were tasked with locating, tagging, and then highlighting and discussing course-related materials using Diigo, a social bookmarking tool. Three different tagging approaches were tested: dictionary only, freestyle only, and dictionary + freestyle. Analysis focused on accuracy, rates of student tagging, and popularity of different tag types. Findings show that most students were able to tag with high rates of accuracy after a single brief lesson. The dictionary-only approach led to fewer tags overall as well as fewer single-use tags than freestyle tagging. It also resulted in students applying useful classes of tags, such as type of content, that did not emerge within the freestyle tag groups' folksonomies. However, freestyle tagging was not without its merits, and it provided opportunities for students to include tags that reflect relevant interests and more specific topics that were not addressed in the tag dictionary. The combined approach, if carefully taught and applied, appears to have the greatest potential for supporting student information literacy skills.

Keywords: higher education, information literacy, social bookmarking, tagging

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Effective Tagging Practices for Online Learning Environments: An Exploratory Study of Approach and Accuracy

Online learners generate a tremendous amount of content, whether in the form of personally written messages or shared online resources (Dennen, 2016). Sifting through this information to find topically relevant contributions can be a daunting task. Students suffering from time constraints may struggle to identify the most pertinent readings and discussion questions in a class (Chen, Pedersen, & Murphy, 2011), and learners benefit from some form of guidance in this process (Buder, Schwind, Rudat, & Bodemer, 2015). In order to help learners effectively and efficiently sift through the content generated by an online class, a means of organizing and identifying relevant items is necessary.

One approach to the organization of online resources is the use of tags. Tags are simply keywords used to label or classify a file or similar content object. Computer-based tagging systems, in which classification keywords are applied to content objects and stored in a database, make bodies of information more easily searchable. Leonardi (2017) proposed that the use of tags—in particular emergent or user-generated ones—can help group members find both the knowledge that they are looking for and previously unknown items of interest. Various online applications support tagging, including discussion forums, social media platforms, and social bookmarking tools. Although tagging processes and formats may vary slightly from tool to tool, the concept remains the same.

For students, the benefits of tagging systems may be twofold. First, when students tag items to share with their classmates, the act of selecting a tag, whether from a predefined or user-generated source, requires that students give careful consideration to why they are sharing the item, how it relates to the course content, and how their classmates are most likely to search for it. Second, when students use the collection of resources shared by peers, tags can help them effectively find those items that are most relevant to their interests and needs.

Learning to tag may hold other benefits for contemporary students. Digital literacy in general, and information literacy more specifically, has long been considered an important 21st-century skill. The American Library Association's (2015) Framework for Information Literacy for Higher Education suggests that learners should be able to draw upon various searching strategies, including keywords. Broadly construed, tagging also has been tied to the development of critical thinking skills (Schellens, Van Keer, De Wever, & Valcke, 2009). Tagging skills will help learners throughout their lives, whenever they engage in information identification, storage, or retrieval tasks.

Tagging is only effective when the end users are able to efficiently find the information that they seek. Although students may be familiar with the concept of tagging from using hashtags on social networking sites, they may not independently be able to tag effectively in an online learning context. In this study, students were taught how to tag during a five-week resource-sharing and discussion activity hosted in a social bookmarking tool. The purpose of this exploratory study was to examine how students tagged learning resources, focusing on accuracy and rates of tag application, and whether three different tagging approaches (dictionary, freestyle, and dictionary + freestyle) yielded different tagging results. A secondary focus was to examine student perceptions of the utility of tagging while collaboratively building a knowledge base, searching the knowledge base, and discussing relevant resources within a social bookmarking tool.

Background

Social bookmarking applications, such as Diigo, the now-defunct but previously popular del.icio.us, and Pinterest, provide support for sharing links to online resources with others. Beyond link sharing, these tools facilitate the addition of notes and allow users to classify resources. From a user perspective, social bookmarking is an activity that involves locating Internet-based materials, classifying and describing them, and sharing the annotated URL for those materials within a web-based tool for later retrieval by other Internet users.

The classification part of the social bookmarking process uses tags. Tags are a form of descriptive metadata, or data that provide information about an object so it can be effectively stored with similar items and retrieved as needed (Pomerantz, 2015). Tagging is a standard part of the sharing process enabled by social bookmarking tools, although many people are familiar with the

concept from popular social media platforms, such as Twitter. Twitter in particular popularized a variant of the practice, called hashtagging. Twitter tags use the hash or pound sign (#) immediately preceding the tag to denote a keyword for searching and aggregation. Other tools, however, tend to just use a word without a symbol.

This section addresses both the role that social bookmarking, and tagging more specifically, play in the educational setting. Additionally, it provides information about tag approaches and the relationship of expertise to tagging practices.

Social Bookmarking and Tagging in the Educational Setting

There are multiple ways in which social bookmarking might be implemented in a class setting. Social bookmarking tools may be used to support either individual or collaborative bookmarking processes (Kiu & Lim, 2017). Instructors may lead the activity, using social bookmarking tools to collect and share relevant online resources with their students (e.g., Saeed, Yang, & Sinnappan, 2009; Farwell & Waters, 2010). Alternately, learners may be engaged directly in the process of locating, sharing, and tagging resources (e.g., Im & Dennen, 2013; Colwell & Gregory, 2017). Whether actively sharing or passively consuming, learners have been found to be successful with knowledge building through social bookmarking activities (de Carvalho, Furtado, & Furtado, 2015).

Social bookmarking in the academic context is an underresearched area, leaving uncertainties about its overall utility in education despite various proclamations that it is a useful learning tool and activity (Sera, 2015). In one study, students were found to be apprehensive about using a new tool and engaging in social bookmarking (Farwell & Waters, 2010). Many students in this class, in which the instructor bookmarked and shared various resources with students, ended up having a positive experience. However, they struggled with the concept of tagging. In another study, several students did not participate because they considered it the instructor's responsibility to find and share learning resources (Kear, Jones, Holden, & Kurcher, 2016). An exploratory study of student-led social bookmarking in Diigo, student use of and contributions to the group knowledge base varied between sharing and commenting, and a coherent folksonomy emerged toward the end (Im & Dennen, 2013). Although these studies and others focus on disparate learning activities and outcomes, they demonstrate the position that social bookmarking and tagging activities have come to play in the learning experience.

Tagging serves both individual and collective pedagogical purposes. Individually, tagging activities promote self-regulation within the learning process (Cao, Kovachev, Klamma, Jarke, & Lau, 2015), whereas collaborative tagging activities are useful in classrooms because they promote peer engagement around content artifacts, and the act of tagging requires reflection (Bateman, Brooks, Mccalla, & Brusilovsky, 2007). Additionally, students working in the same topical area can learn from each other's processes and paths when they are documented by tagging activities (Klašnja-Milićević, Vesin, & Ivanović, 2018). In other words, tags provide evidence of what materials others have seen and what sense they made out of these materials. Looking to the future, learner-generated tags, shared in a collaborative system, have been suggested as one means of generating personalized recommendations within an e-learning system (Klašnja-Milićević, Ivanović, Vesin, & Budimac, 2018).

Forms of Tagging

For social bookmarking lessons to succeed, students need to be able to work with tags. Most popular social bookmarking tools use tags that are applied at the document level (Bateman et al., 2007). When a collection of tagged resources is amassed, users can sort and search through those resources using the tags. Most tags are nouns indicating the item's content. However, tags are also used to identify type of material (e.g., blog, article), author, personal judgment or sentiment (e.g., stupid, inspirational), self-reference (e.g., my stuff), and task organization (e.g., to read, job search) (Golder & Huberman, 2006). Tags that are general in their approach to classification tend to have higher rates of entropy than specific ones, the latter appearing less frequently in a tag database (Klašnja-Milićević, Ivanović, et al., 2018).

Tagging approaches may be freestyle, allowing users to generate their own tags and collectively develop a folksonomy, or constrained by a dictionary of predefined tags. Freestyle tagging allows knowledge to be represented in unlimited ways, outside the confines of what authoritative figures determine is useful based on social and cultural biases. In addition, freestyle tagging allows topics to develop over time due to increasing information sophistication, levels of distinction, and social trends (Lin & Chen, 2012). However, freestyle tagging is plagued by synonymy (Golder & Huberman, 2006), where multiple tags having similar meanings (e.g., teacher, teachers, educators, and tutor) are applied, and each synonymous tag is linked to different resources. Misspellings and personal naming conventions in a freestyle system further complicate tag searching. In a random sample of tagged items from two social media sites, Guy and Tonkin (2006) found a high rate of user tagging errors. In another study, tag reuse and differentiation in a learning object repository were found to stagnate over time (Zervas, Sampson, & Pelliccione, 2016).

In contrast, tag dictionaries provide standardized naming conventions and reduce the redundancies common in freestyle tagging. However, the recommended terms in a dictionary system may be insufficient to fully capture the richness and diversity of resources that individuals find and share, or the ways in which they may need to classify them. Expert taggers report using both recommended tags from a dictionary along with additional terms in order to sufficiently categorize resources (Panke & Gaiser, 2009).

Accuracy of Novice Tagging

Tags can be generated and applied by experts, authors, machines, or end users. Some of the issues related to tagging include the question of who should generate tags and whether consumers of content (as opposed to authors or experts) are reliable taggers. The belief that experts are more accurate taggers runs sufficiently deep that there is a patent for a computer-based system that will revise a document's tags based on new tagging information, giving the greatest weight to tags generated by experts (Bagwell & Vasudevan, 2017). Expert practices often are considered the benchmark for examining how other people and entities apply tags.

When authors apply keywords to their manuscripts, as is the norm for many academic publications, they tend to focus on main ideas or themes within their manuscript. In a study of end-user tagging practices, the tags of typical users were found to be fewer and more general than the author-selected keywords (Heckner, Mühlbacher, & Wolff, 2008). Another study showed that expert taggers usually apply seven or fewer tags per item (Panke & Gaiser, 2009). When comparing students and experts, Bateman et al. (2007) found that students created more tags overall as well as more unique tags than experts. At the same time, students did not integrate expert

tags when those were provided to them. Similarly, another study found that medical experts used fewer and more direct tags than laypeople when cataloging the same images (Phoebe, Wei-Chung, Kai-Ying, Chia-Chi, & Shing, 2016). These studies suggest that experts are more economical than novices in their tagging practices, and that they draw upon a shared knowledge base.

However, when compared to machines, students and text-mining systems were found to be in agreement two thirds of the time (Bateman et al., 2007). This finding corroborates another study of how participants applied descriptive versus assessment tags (Mamykina et al., 2011). The researchers found that participants were inclined to use whatever kind of tags best matched the vocabulary words that they had at hand, suggesting that for novices the tagging process is driven by contextual cues provided directly in the content being tagged. Finally, when tagging material within the context of a class, student tags were found to be germane and useful (Bagwell & Vasudevan, 2017; Gorissen, van Bruggen, & Jochems, 2015). Furthermore, the tags that they applied to instructional videos aligned with those applied to the same videos by fellow students as well as experts. Collectively, these prior studies suggest that students tag differently from experts but that the difference in this context is not necessarily a problem.

Methods

Research Questions

In this exploratory study, we developed and tested a learning activity using Diigo, a social bookmarking tool. The following research questions guided this study:

- After brief instruction, how accurately can learners apply tags to shared content within a social bookmarking tool?
- How do tag accuracy, rates, and types differ based on tag approach?
- What were student impressions of tagging and its utility in the class setting?

Participants and Context

Participants were 99 undergraduate students enrolled in six sections of an educational technology class for preservice teachers during the fall 2016 semester (see Table 1). This class met requirements for both the teacher education curriculum and the university's general education computing course. Enrollment was not restricted by major; students from across the university were free to enroll in the class. However, most students ($n = 69$; 87%) reported plans to work in education after graduation. Data on student age was not collected, but based on past terms we know that students in this class typically range in age from 18–22.

Table 1
Overview of Participation and Demographics by Course Section

Course section	Tag approach	Participants in section	Participants completing survey	Gender	Class standing
Section 1	Dictionary only	17	16	Female: 15 Male: 1	Freshman: 4 Sophomore: 10 Junior: 0 Senior: 2
Section 2	Dictionary only	11	10	Female: 10 Male: 0	Freshman: 5 Sophomore: 5 Junior: 0 Senior: 0
Section 3	Freestyle only	21	20	Female: 18 Male: 2	Freshman: 4 Sophomore: 12 Junior: 2 Senior: 2
Section 4	Freestyle only	17	14	Female: 14 Male: 0	Freshman: 2 Sophomore: 12 Junior: 0 Senior: 0
Section 5	Dictionary + freestyle	11	7	Female: 7 Male: 0	Freshman: 2 Sophomore: 3 Junior: 2 Senior: 0
Section 6	Dictionary + freestyle	22	12	Female: 11 Male: 1	Freshman: 4 Sophomore: 4 Junior: 2 Senior: 2
Total		99	79	Female: 75 Male: 4	Freshman: 21 Sophomore: 46 Junior: 6 Senior: 6

The study was approved by the university’s Institutional Review Board. Approval was given to access the full archive of tags and tag use in each class’s Diigo group. Additionally, 79 students consented to participate in a survey about their experience in this lesson and gave us permission to look specifically at their tag use (see Table 1).

The course instructors had little to no prior experience using Diigo. Those who had used it had done so in a very unstructured manner in another class. The researchers and instructors had a meeting prior to the implementation of the Diigo unit to prepare the instructors to use Diigo, set up their accounts, and discuss how they would teach it to their students. Instructors were assigned to use one of the three tagging conditions at this time. Common instructional materials (e.g., slides and handouts) about Diigo use and tagging were provided to all instructors.

Each class had a separate Diigo group that was used for the unit. These groups were set up by the authors, who shared moderator status with the course instructors. Once the researchers had the Diigo groups appropriately set up and loaded with examples, they did not enter the space again until the unit had concluded and data were ready to be saved. Instructors helped their students set up Diigo accounts and then invited them to join the group.

Diigo Unit and Tag Dictionary

For the Diigo unit, students were instructed to find high-quality online sources (articles, blogs, etc.) based on the topic of the weekly lesson. Then, they assigned a tag (or tags) to describe and organize each source. During some weeks they further highlighted and discussed these sources. Diigo, as a tool, was not the sole focus of the unit; in addition to developing bookmarking and tagging skills, there were topical learning objectives related to the content students were tagging.

Formal instruction on how to use Diigo was provided to students at the outset of the first lesson. Prior studies have found that university students, regardless of level, generally do not understand social bookmarking and tagging activities (Frisch, Jackson, & Murray, 2013; Neier & Zayer, 2015), and they need instruction both about the underlying purpose of social bookmarking as well as how to do it effectively (Taha, Wood, & Cox, 2016). During the first week, students were taught and tasked with generating bookmarks along with tags and descriptions of each item bookmarked. In subsequent lessons, additional Diigo features were taught and used (see Dennen, Cates, & Bagdy, 2017, for a fuller description of the activity). Tagging was a consistent activity across all five weeks.

The tag dictionary was developed by the researchers based on the topics addressed across the five topical lessons in the Diigo unit. The five topics addressed in these lessons were Academic Software and Apps, Web 2.0, Teacher Productivity Software and Apps, Assistive/Adaptive Technology, and Teacher Professional Development. In addition to topical tags related to each lesson, there were also tags to identify the type of resource being bookmarked (e.g., video or article) and the audience or application for the resource (e.g., elementary). Because Diigo limits the number of tags that can be entered into the preset dictionary, the tag dictionary was provided to students as a linked Google Doc. Students in the dictionary groups had access to this Google Doc and were told to copy and paste or type in the tags from the dictionary when they bookmarked items in Diigo. Students in the freestyle-only group could not access the dictionary.

Data Collection and Analysis

Data collection focused primarily on tag archives from the class Diigo groups. Tag dictionaries were downloaded and cleaned. Specifically, instructor-tagged items that had been done as examples for the students needed to be removed. Unfortunately, a technical error resulted in the inability to collect the archives from one of the classes (Section 6). Students were surveyed at the end of the term about their experience using Diigo and their impressions of tags. The survey was conducted online and contained three demographic questions, two questions about prior experience with Diigo and social bookmarking, and seven items about their experience with Diigo in the class (see Table 7 for these items). Additionally, the researchers kept notes based on feedback received from instructors during the unit, and some of the class sessions were observed.

Data analysis focused on counting tagging rates, comparing tags to the dictionary, and finding tag similarities and differences among the course sections and the ways in which and frequencies with which students selected tags. For survey data, closed items were examined for frequency distributions and central tendency, and open items were examined thematically.

Results

Rates of Tagging

Students generally applied tags to bookmarked items as requested within the assignment. However, as shown in Table 2, several items went untagged in each group. The average number of tags per item ranged from three to five for four of the groups, with only one group (Section 2) having both a lower number of tagged items and lower number of tags applied per item. This instructor also had a small class and reported technical difficulties using Diigo. Similarly, this instructor’s students commented on technical problems during the survey. Based on some of those comments, we believe that the technical part of the instruction (e.g., how to log in and use Diigo) may have gone awry within this section. We suspect that both the lower rates of tagged items and tag use may reflect the frustrations that class members experienced.

Table 2
Tags Per Item

Section	Tag condition	# of student-tagged items	# of tags applied	Mean tags/item	Items without tags
1	Dictionary	73	286	3.92	13 (18%)
2	Dictionary	30	52	1.73	13 (43%)
3	Freestyle	50	162	3.24	18 (36%)
4	Freestyle	65	274	4.22	7 (11%)
5	Dictionary + freestyle	65	266	4.09	15 (23%)
Total		283	1,040	3.67	66 (23%)

Tag Accuracy

Tag accuracy was defined as the student’s ability to apply a tag without error. To accurately apply a tag required understanding the rules of tagging within Diigo. Accuracy does not, in this instance reflect whether or not the tag reflects the content of the resource to which it was applied. As shown in Table 3, tagging accuracy rates were fairly consistent across groups and also were quite high. Among the errors noted were the following:

- adding the hashtag symbol (#) to tags, as is the norm on Twitter;
- adding other characters or symbols to tags (e.g., “subject: math” and “elementary_math”);
- misspelled tags (e.g., “teachers” rather than “teacher”; “software” rather than “softwre”);
- separated compound word tags (e.g., creating two separate tags—“professional” and “development”—rather than one “professional development”); and
- compound word groupings (e.g., creating a tag with two separate words connected, like “professionaldevelopment”).

The last two issues listed above, where two-word tags were either combined as a single word or separated into two different tags, were the most commonly seen errors and account for the bulk of the errors in Section 1. These errors suggest that students failed to grasp the appropriate way to enter a multiple-word tag into Diigo, or that they assumed spaces were not possible within tags. Some platforms, like Twitter, use compound-word groupings in tags. In contrast, Diigo allows users to create multiple-word tags by using quotation marks.

Table 3

Summary of Tag Accuracy

Section	Tag condition	# of tags	# of tags with errors	Accuracy rate
1	Dictionary	286	45	84%
2	Dictionary	52	3	94%
3	Freestyle	162	8	95%
4	Freestyle	274	12	96%
5	Dictionary + freestyle	266	9	97%
6	Dictionary + freestyle	N/A	N/A	N/A
ALL		1,040	77	93%

Note. Archive was not available from Section 6.

Not included in the accuracy count, although seen across every group, are instances of tag synonymy due to the appearance of both singular and plural form. The most common instance, appearing in all of the groups, was “teacher” and “teachers.” Although we did not see any personal tags with cryptic meaning, there were a few students in the freestyle conditions who used sentiment tags, such as “fun” and “helpful.”

During our analysis of bookmarked items, which was a manual process, we noted that no course section or condition stood out as being the best or worst at tagging. None of the students had prior experience with Diigo, and only two reported previous experience with social bookmarking. However, there were standout students, both good and bad, within each course section. Each class had exemplary taggers, who had few or no tagging errors. These same students also applied more thoughtful, meaningful tags, whether in a dictionary or freestyle taggers. At the same time, each class had students who made frequent tagging errors or who continuously neglected to tag the items they shared. This was the case in Section 1, which had the highest rate of errors.

Tag Popularity and Dictionary Use

The groups that had the tag dictionary available to them made use of those tags. Only five of the 59 dictionary tags were not applied across the five lessons (see Table 4). We checked the tags used by the freestyle-only groups as well to see whether they naturally used the same tags as were in the dictionary. Their tags matched 42% of the dictionary tags. Notably, students in the freestyle-only groups did not make heavy use of tags for audience/application, nor were they as likely as dictionary groups to classify their items by type of resource. This finding shows that these students were oriented toward thinking about content when tagging but did not independently consider application or resource type. In contrast, although these are useful tags, students may not intuitively and independently consider using them. Either dictionary support or explicit instruction to develop these types of tags may be necessary to increase their prevalence.

Table 4
Overview of Tag Dictionary Use by Tag Type

Tag type	# of tags	# used by dictionary groups	# unused by dictionary groups	# used by freestyle-only groups
Resource type	8	8	0	4
Audience/application	9	8	1	2
Content	42	38	4	19
Total	59	54	5	25

Table 5 shows the most frequently used tags by course section and denotes which of those tags were included in the tag dictionary. Section 2 again stands out, this time because it is apparent that learners were not following the directions of their condition. Section 2 had a tag dictionary, but only two of the six most highly applied tags in this section appear in the tag dictionary. Technologically, we were unable to prohibit dictionary-only-condition students from applying freestyle tags in Diigo, and students in this class appear to have not heavily used the dictionary. It is possible that they did not refer to the dictionary at all and may not have been aware of it if their instructor did not introduce it as requested; the two dictionary tags that these students did use may appear simply out of coincidence.

Table 5
Most Frequently Used Tags by Course Section

Section 1 (D)	Section 2 (D)	Section 3 (F)	Section 4 (F)	Section 5 (D+F)
teachers (37) [°]	disabilities (6)	education (13)	education (28)	education (14)
article (19) [°]	apps (5) [°]	professional (7)	technology (17)	k-5 (14) [°]
apps (16) [°]	productivity (4)	resource (7)	educational (14)	teachers (12) [°]
game (13) [°]	technology (4)	software (7)	apps (13) [°]	learning (11)
k-5 (13) [°]	learning (3)	development (6)	interactive (11)	practice (10)
	teachers (3) [°]	interactive (6)	learning (11)	

Note. Dictionary and freestyle (D+F), Freestyle only (F), Dictionary only (D).

[°]Included in the tag dictionary

Across the three sections that explicitly used freestyle tags, there was a high rate of general tags. “Education” was most frequent in all three classes and yields very little descriptive information. Given that the course was about education, one would automatically expect most or all of the tagged items to be classified as education related. In Section 1, which used the dictionary, tagging was more heavily focused on identifying type of resource and audience/application.

In examining the number of times each tag was used across all course sections, single-use tags accounted for a sizable number of tags overall (see Figure 1) and a notable percentage of tags in all but one section (see Table 6). The single-tag rate ranged from 35–40% in the conditions that included freestyle tagging and also in the section that was assigned to use the dictionary but deviated from it. The one section with fewer single-use tags (Section 1) was assigned to the

dictionary condition and, based on a review of their tags, relied on the dictionary for their tagging activities. In observations, that particular instructor was rather emphatic during the instruction that students must make use of the tag dictionary. As can be seen in Table 5 and Figure 1, there were a handful of tags (18 in total) that were applied 10 or more times.

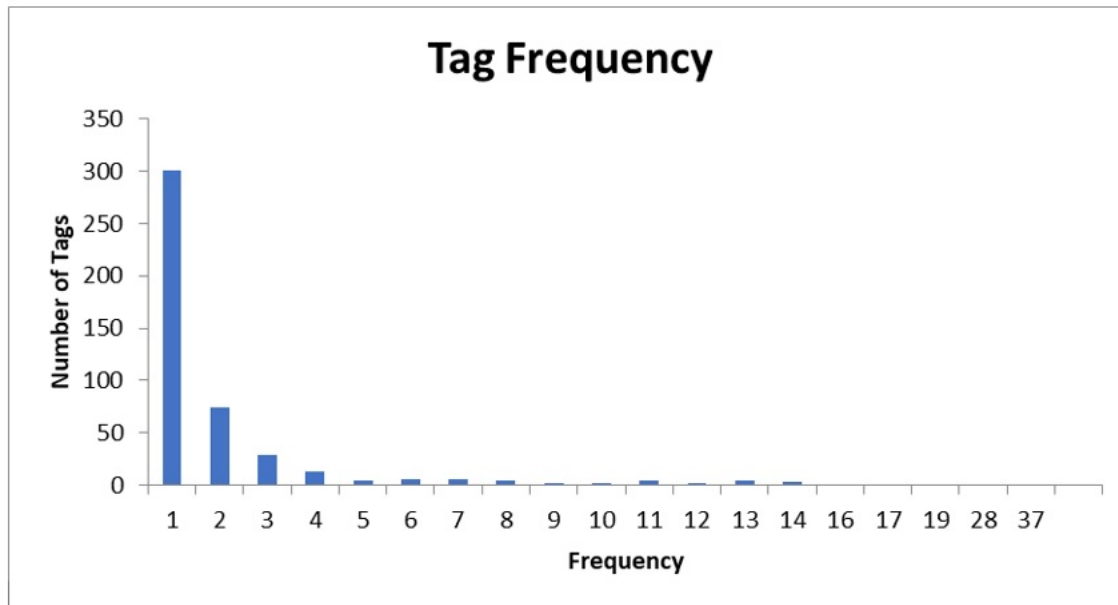


Figure 1. Frequency of tag use (aggregate across sections).

Table 6
Rates of Single-Use Tags

Course section	Tag approach	Single-use tags	
		<i>n</i>	%
Section 1	Dictionary only	35	13
Section 2	Dictionary only	19	37
Section 3	Freestyle only	64	40
Section 4	Freestyle only	96	35
Section 5	Dictionary + freestyle	87	33

Survey Findings

At the end of the course, students completed a brief survey asking a few questions about their experiences using tags (see Table 7). Across all sections students largely agreed ($n = 68$; 86%) that tags provide a meaningful way to save links, although 20 students (26%) indicated that they felt tagging was at least somewhat a waste of time. To a lesser degree, students indicated that they carefully chose which tags to apply when sharing an item ($n = 61$; 77%). Most likely to disagree with this statement were students in the dictionary only sections. Similarly, 60 students (76%) felt that it was easy to determine which tags to use, with the dictionary groups again reporting the greatest disagreement.

When asked about using tags to search through resources shared by classmates, 55 students (70%) reported doing it, and 54 students (72%) felt that tags would help them decide which of their classmates' shared resources they should look at. Finally, 58 students (74%) said that tags in general helped them locate relevant resources. In response to this question, students likely considered items shared and tagged by the instructor in addition to items shared and tagged by classmates. Several students ($n = 10$; 13%) expressed ambivalence on this item, and once again the dictionary-only group stood out as the only dissenters, with six students (24% of the respondents from this condition) reporting that they disagreed.

Table 7
Summary of Survey Responses

Item	Response		
	Agree	neutral	Disagree
Tags provide a meaningful way for saving links.	68 (86%)	5 (6%)	6 (8%)
I found using tags to be a waste of time.	20 (26%)	14 (11%)	45 (63%)
I carefully chose which tags to apply to the items I shared with the class.	61 (77%)	7 (9%)	11 (14%)
It was easy to determine which tags to use when sharing a link.	60 (76%)	13 (10%)	6 (13%)
I used the tags to search through the resources shared by my classmates.	55 (70%)	9 (11%)	15 (19%)
Tags helped me locate relevant resources. *	58 (74%)	10 (13%)	10 (13%)
I used tags to help me decide which of the links shared by classmates I should check out. **	54 (72%)	11 (14%)	11 (14%)

Note. There were 79 survey participants. Two questions were not completed by all participants (* $n = 78$, ** $n = 76$).

Discussion

The students in this study, like students in similar studies (e.g., Frisch, Jackson, & Murray, 2013; Wood et al., 2014) were social bookmarking novices at the beginning of the term. Even after instruction and five practice sessions, they would still not be considered experts. The struggles that some students experienced with accurate tagging combined with the application of overly general tags by students in freestyle conditions confirms the need for student training to effectively use tools such as Diigo (Wood et al., 2014). Two approaches have been suggested for improving tag literacy: educating users so they can engage in more effective tagging and developing technology-based systems that better support the tag selection process (Guy & Tonkin, 2006). We believe that both of these approaches are necessary and should work in tandem. Although a sophisticated tool that provides tagging and searching assistance is ideal, students will be faced with situations in their lives where they must make tagging and searching decisions without assistance.

The tagging errors that occurred were not surprising. Researchers in other studies similarly found a tendency for some individuals to use phrases for tags or engage in other inefficient procedures (Mamykina et al., 2011), and sloppy tagging practices, such as misspellings and compound-word issues, in folksonomies (Guy & Tonkin, 2006). This finding confirms the need to teach learners how to generate and apply tags and the rationale for stressing the use of succinct keywords rather than phrases.

We anticipated a large number of single-use tags, particularly in the freestyle tagging sections. Like Guy and Tonkins (2006), we had thought the rate might be even higher when

students were engaged in freestyle tagging. The great variance in rates of reuse of tags was not surprising. While overall reuse may be low, certain tags may be reused at high rates (Zervas et al., 2016), and the histogram for overall tag use rates (see Figure 1) mimics the one created by Guy and Tonkins (2006). Single-use tags are not necessarily problematic, especially when individuals are beginning to amass tags in a group knowledge base. However, in order to reduce redundant tagging, students could be encouraged to look through existing tags and reuse them to the extent the tags are relevant.

There are many potential explanations for the range of tagging expertise among the students and the various tagging errors that occurred within the class. Although the students did not have prior experience with Diigo, and all but two indicated no prior experience with social bookmarking, we did not ask about prior experience with classification systems in other tools or settings. Students with this type of experience may have been able to transfer this prior knowledge to the lesson tasks and, as a consequence, may have been more successful. Course attendance also may have played a role. We know from instructor reports and our involvement in the Diigo account approval process that some students were absent during the initial lesson, in which tagging was the main focus, and some did not have an account in Diigo until the second or third lesson. This was not a large number of students; although we do not have a precise number, we would estimate it at 5–10% of the students across all sections. Those students may have struggled more than their peers to identify and apply pertinent tags.

In these findings, we see value in both the dictionary and freestyle approaches. The use of a dictionary helped students select and apply descriptors that ultimately would be useful to another person seeking resources on a technology integration topic. Thinking about the activity as an end user rather than as a tag contributor, it is clear that tags such as “K-5” would provide more useful information than “education.” Additionally, the tag dictionary appeared to limit the number of single-use tags within the overall collection. However, the dictionary is only of use if it is well created and contains content-, resource-, and audience-specific tags. The tag dictionary also would function better if it were integrated directly into the tool (i.e., users choose tags by clicking on them rather than typing them in, which introduces potential error).

The freestyle approach is helpful because it allows the users to customize the tagging process and include classifications that are personally meaningful and to tag items that are perhaps tangentially relevant to the overall purpose but nonetheless important. Of note was the inclusion and multiple uses of the tag “disabilities” in Section 2. This tag did not appear in the dictionary, but the six applications of this tag suggest that one or more class members had a specific interest in this area.

The dictionary + freestyle approach appears to combine the best of the other two approaches so long as users work in a dictionary-first manner. In other words, the use of a shared dictionary could help reduce the number of single-use tags based on synonymy and increase the use of classifications, such as type or application of resource. At the same time, freestyle tags could be added to extend beyond the scope of the dictionary and to allow for even more specific tagging. Students in one study found tags more useful when looking for general topics than when searching for resources with great specificity (Sinclair & Cardew-Hall, 2008). Tag dictionaries, while they ideally eschew overly general or self-evident tags (e.g., the tag “education” in the context of an education class) may still be a bit general for users seeking resources on narrow topics.

Student survey results show generally positive sentiments toward tagging, although we note that 20 students (20% of the potential participants) declined to participate in the survey. It was not surprising to learn that students found tag application useful but were not highly interested in looking at the contributions of others within the Diigo group. This finding confirms an earlier study of a student communal knowledge base (Wheeler, Yeomans, & Wheeler, 2008). Additionally, while the assignment given to students in this class did require them to comment on shared resources, it did not put students in a strong position of interdependence for compiling and reviewing shared resources. A student could have completed the lessons by simply choosing a resource in Diigo at random and commenting on it.

Limitations

This study has various limitations, representing a combination of lesson design, research design, and tool factors. The students were not graded on the quality of their tagging or their contributions, which may have resulted in some students being unmotivated to fully engage in the activity. Students would not have received formative feedback on their tagging activities unless they explicitly sought it from their instructor, so students who did not fully understand accurate tagging practices from the initial instruction would not have been corrected unless they observed that their peers were tagging differently. Additionally, instructor lesson delivery and facilitation varied despite providing training and instructional materials. Greater control over this element would be desirable in a follow-up study.

Our inability to collect tag archives from one class section was unfortunate and left us without two examples of classes using the combined Dictionary + Freestyle conditions. Because we neither controlled for instructor nor observed all of the class sessions in which Diigo was taught, we are not confident that all classes received equal instruction on Diigo use and tagging. In particular, we believe that the instruction in Section 2 deviated from the plan because of the technical struggles students reported and the degree to which their tagging activities deviated from the assigned condition.

Diigo proved to have a limitation that we did not anticipate when we designed this study. Specifically, the built-in tag dictionary had a limited capacity; only 20 tags could be added to this dictionary. We had wanted to provide the dictionary tags directly in Diigo for the dictionary condition sections so they could select the tags rather than type them in. Although we tested the dictionary feature prior to study design, we did not test it with the full tag dictionary but rather only the tags needed for Lesson 1. When we realized that Diigo was not going to allow us to build a larger dictionary within the tool, we decided to use a Google Doc to provide the dictionary terms instead. This approach, although functional, made dictionary-based tagging a bit cumbersome. Students needed to have two browser windows open: one to view the dictionary and one to use Diigo, so that they could manually type or copy and paste the tags they wished to use from the dictionary. This workaround may have led some students to dismiss using tags, or to stray from using the tags suggested in the dictionary.

Conclusion

In this study, tagging was embedded within a larger instructional activity. An advantage of this approach was its authenticity. Students were not focused solely on tagging, but rather tagging was integrated alongside other complementary activities, such as searching for relevant resources

and discussing those resources with peers. The integrated nature of this activity accounts for the relatively low number of tagged items shared by each class; had students been solely engaged in tagging items, they likely would have tagged more items during their class sessions. They also might have spent more time and effort considering each tag. Although metadata specialists may spend time focused solely on item classification tasks, for most people tagging is usually embedded within the workflow of activities that rely on a medley of information literacy skills.

Findings from this study show that most students can become competent taggers with relatively little instruction. Students benefit from dictionary-based tagging systems, which scaffold the tagging process by suggesting tags that are relevant to the course topic and activities. They also benefit from the ability to generate their own tags. These user-created tags, so long as they are sufficiently meaningful to others, add richness and specificity to the knowledge base and may help other learners identify relevant subtopics within the course. To minimize synonymy, learners should be encouraged to develop and follow tagging conventions within the class (e.g., always use singular or root form of a tag) and to check how others have tagged similar items before creating a new tag.

In closing, we believe that the potential of social bookmarking and tagging has yet to be fully understood or exploited in formal learning contexts. However, these skills are important components of information literacy and are used increasingly in professional settings where large quantities of information are being amassed, evaluated, and shared. These skills also are used by professionals seeking to reach a specific audience through the effective use of tags or metadata. More research is needed to systematically explore the best ways to teach these skills to students, how to fully develop and support these skills through learning activities, and how these skills go on to support lifelong learning. Future studies might compare these types of tag dictionaries under experimental settings and extend their use to alternate online learning activities, such as discussion.

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Emerging Technologies: It's Not What *You* Say – It's What *They* Do

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Abstract

This paper is provided for the *Online Learning* journal 2018 Special Conference Edition. It was initially presented at the 2018 OLC Innovate Conference in Nashville Tennessee. In this article, we will explore various emerging technologies. It is important to note that the authors believe that learning is not a complete circle when evaluated by what educators do, the technologies we use, or how we communicate our knowledge to our students. Learning is only successful when we fully assess the impact of our preparations and presentations on student outcomes. Students need the opportunity to actively participate in the *doing* of learning. Modeling the literacies needed to enable us to skillfully meet the needs of our future world through strong use of technologies in a heutagogical setting enables learning success.

Keywords: emerging technologies, heutagogy, high-impact learning

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Emerging Technologies: It's Not What *You* Say – It's What *They* Do

Can a student learn while commuting in an autonomous car? Can a robot teach my class? Is what I tell my students making an impact in my class? How can I create learning experiences that will move students toward the future? In this paper, we explore these and other questions related to the intersection of the latest technology trends in higher education. We consider how they will impact both the online and traditional classroom modalities while focusing on student-centered learning and heutagogical practices. We provide a brief overview of a few of the emerging technologies that will encourage us to explore new ways to lecture to a class and provide students with high-quality, impactful learning engagement. We consider how we might utilize emerging technologies to provide students with learning experiences through *doing*.

Emerging technologies support the theory of heutagogy by making learning more pervasive and ubiquitous, giving learners more opportunities to determine what, where, when, and with whom learning takes place. The concept of heutagogy expands our current thinking of pedagogy and andragogy to look at self-determined learning (Gerstein, 2014). Connecting information from a variety of fields and individuals is necessary to add depth and breadth to the self-determined learner's knowledge base. As educators, we can create the curiosity to find and explore connections between many sources while using emerging technologies that can lead learners to new knowledge and enhanced learning. The transition from pedagogy to heutagogy is depicted in Figure 1 (Blaschke, 2012).

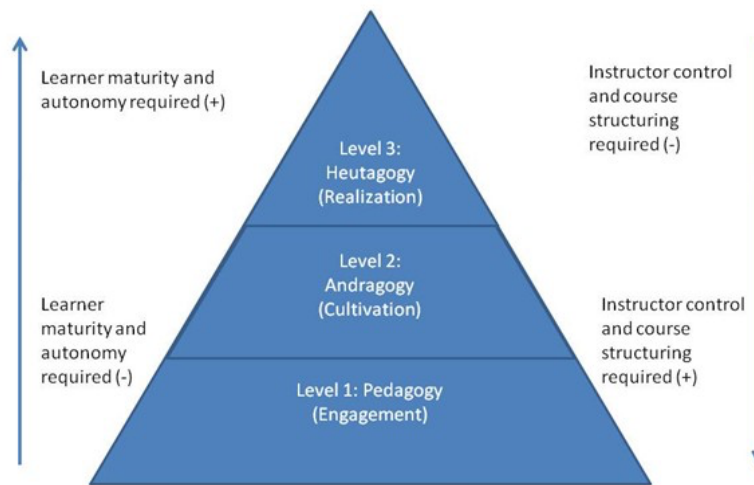


Figure 1. Progression from pedagogy—andragogy—to heutagogy. Adapted from “Heutagogy and Lifelong Learning: A Review of Heutagogical Practice and Self-Determined Learning,” by L. M. Blaschke, 2012, *The International Review of Research in Open and Distance Learning*, 13(13), p. 60. CC-BY.

This article considers some of the most recent trends and new learning technologies, including artificial intelligence, virtual reality, augmented reality, and experiential reality, with exemplars of how the technologies being discussed can benefit the self-determined learner. It explores the definitions, continuum, and characteristics of pedagogy, andragogy, and heutagogy and their impact on student-centered teaching strategies. The focus centers on the strategies connected to a student-centered teaching approach. What students *do* is far more important than what we, as educators, say. These technologies allow students to become active participants in the acquisition of knowledge.

Artificial Intelligence

Artificial intelligence (AI) may be one of the most significant game changers for higher education. Professor Ashok Goel created Jill Watson, an AI robot who learned to act as an exemplary TA for Goel's large enrollment classes at Georgia Tech (Maderer, 2016). Watson, as the teaching robot is most commonly referred to, was a high-performing TA that indicated that certain responses could be learned and programmed for reuse as students asked questions. In 2017, Hubert, another AI robot, was launched. Now, Hubert can organize and synthesize materials for instructors. Hubert is able to help faculty members determine how to improve their courses by

assisting with student evaluation and feedback (Lieberman, 2018). This tool remains in beta version and has some known need for future development but may be able to assist faculty members by quickly disseminating information from evaluations to assist with building a better learning experience.

In many ways, elements of AI have become ubiquitous in our everyday lives. Hannay (2014) asserted that computer image recognition, text-to-speech processors, cloud-linked applications, and even self-driving cars are examples of AI developments that augment human intelligence. Opportunities for application of AI technologies abound within higher education. AI technology supports adaptive learning, which in turn affords greater differentiation of instruction to learners. Yet, such technologies are not widely adopted across academia. This may be partly due to a relatively high cost of implementation as well as a fear of losing the human connection in education. The full impact of AI on society and education has not yet been explored, but it continues to be an emerging technological trend with potentially far-reaching impacts (Basken, 2016). AI can assist students with moving through the continuum of learning as foundational materials are learned and specific learning needs are met.

Blockchain

Transforming education through an alternate credentialing system is not a new concept but continues to be discussed as a way to decrease credentialing costs while allowing students high-impact experiences in building skills and critical thinking in their field of study (Horn, 2017). Since the 1970s, institutions that provide pathways to adult degree attainment have utilized forms of prior learning evaluation (Buban, 2017). In a report from the Online Learning Consortium Research Center for Digital Learning (Buban, 2017), six institutional case studies were examined and reviewed related to understanding the definition of alternative credentials and how alternative credentials are used to assist the adult learner in meeting their educational goals.

Blockchain provides a new approach to issuing, displaying, and verifying digital credentials. MIT took this concept and created open source code for others to begin exploring this emerging technology (MIT Media Lab, 2016). Most recently, Southern New Hampshire University began issuing blockchain credentials to College of America graduates (Kelly, 2018). Some unaccredited institutions are using this approach as well, such as Holberton School located in San Francisco, CA, which specializes in software engineering programs through a peer review and project-based learning approach to learning, and Teachur, located in Utah and currently working with a consultant to seek regional accreditation, which offers two undergraduate degrees founded on mastery learning to deliver credentials that are alternate routes to a degree. There are other early adopters of blockchain technology to document and verify records (Ruff, 2016). Building a socioeconomic structure utilizing this technology may impact not only the fundamental structure of credentials and transcripts in higher education but may also significantly impact how those who teach may become credentialed. This is a highly complicated structure that needs much more testing and development before it can ever be utilized to improve our current method of credentialing; however, it is a structure that has its roots in the substance of Bitcoin and thus has some underpinning of stability. Basic blockchain technology offers several advantages for end users, such as improved transparency, faster transactions, greater flexibility, and lower costs. Challenges include security issues, validation concerns, utilization, and implementation costs to institutions offering blockchain credentials (Akram, 2017; Ruff, 2016). Further, student privacy is also a concern (Ruff, 2016). Another major challenge in higher education is to ensure accessibility and the adoption of Universal Design in Learning (UDL) principles in course design and delivery.

Accessibility and UDL

Rapid technological advancements have influenced how higher education is delivered over the past two decades, which is evident in the growth of distance education (Allen, Seaman, Poulin, & Straut, 2016; Linder, 2017). Institutions are offering more online, hybrid, and web-based courses today than ever before. Instructors and students have more web-based technological tools at their disposal. With enrollment growth and technology comes a myriad of issues affecting teaching and learning, such as accessibility and UDL (e.g., see the EDUCAUSE Infographic [EDUCAUSE, 2018]).

Accessibility refers to how environments are designed so that learners with disabilities, such as vision, hearing, or mobile impairments, can use and benefit from that environment (U.S. Department of Health and Human Services, 2018). Although state and federal laws like the Americans With Disabilities Act (ADA) require nondiscrimination toward individuals with disabilities in postsecondary education, many institutions have historically complied with their legal requirements by providing individual student accommodations. For example, a disabilities services office might have provided a typed video transcript to a deaf student after a film was shown in class. Accessibility, however, offers a different approach than traditional accommodations because it benefits not only students with disabilities but all learners from a design perspective. According to the Tennessee Board of Regents “‘accessible’ means that individuals with disabilities are able to independently acquire the same information, engage in the same interactions, and enjoy the same services within the same time frame as individuals without disabilities, with substantially equivalent ease of use” (*Accessibility or Accommodation Training Course*, 2015). Given this definition, the previous example of emailing a student a video transcript after showing the film in class would not qualify as being accessible. Rather, all video content would need to have closed captions as a text-based alternative at the time the video is provided to the entire class. By providing captions, the content is more broadly accessible to all learners. Not only could hearing-impaired students access the video content through captions or transcripts, but students who are English language learners and those working in noisy or quiet environments could also take advantage of the alternative format for improved learning.

When considering examples such as video captioning, accessibility and UDL are often discussed together. That is expected, because a UDL approach to course design anticipates “the presence of students with diverse abilities, disabilities, and other characteristics” (Burgstahler, 2015, p. 32). UDL reflects a paradigm shift in how educators design learning environments. A UDL approach is intentionally more inclusive of diversity among individuals, rather than focusing on the average student (Burgstahler, 2015). Consequentially, the UDL approach tends to reduce the need for student accommodations based on disability.

Researchers at the Center for Applied Special Technology (CAST) developed UDL as a framework for optimizing the teaching and learning process. The UDL guidelines are grouped into three categories, with the goal of developing expert learners who are

- purposeful and motivated (through multiple means of engagement),
- resourceful and knowledgeable (through multiple means of representation), and
- strategic and goal-directed (through multiple means of action and expression) (CAST, 2018).

Guidelines encourage provision of options in each area to make learning materials accessible and applicable to diverse learners; thus, flexibility is a central premise of UDL. Emerging technologies support the practice of universal design as well as the theory of heutagogy by providing learners with more options for consumption of information, engagement, and assessment. Additionally, technologies support improved accessibility in the design and use of common instructional materials.

Augmented, Virtual, and Mixed Reality

Perhaps the emerging technologies that have the most potential to impact higher education are in the areas of augmented, virtual, and mixed reality. Institutions are now experimenting with these tools to build strong pedagogical uses to assist the experiential learning techniques in a variety of disciplines. Bitter and Corral (2014) asserted that this type of technology was pedagogically sound and would become pervasive in education. Additionally, they noted that this type of technology lends itself well to adaption to mobile and wearable technologies. Expanding this immersive technology into the mobile environment supports the movement into a self-determined mode of learning by adhering to the tenet of heutagogy (Blaschke, 2012). Use of mobile devices to engage in anywhere, anytime learning is enhanced through the use of augmented and virtual reality apps. Already, many medical schools are expanding the experience of medical students with combinations of augmented, virtual, and mixed reality, such as the Mixed Reality Lab at Oklahoma State University (<http://trcf52.okstate.edu/x/index.html>).

There are major differences between augmented, virtual, and mixed realities, and the technologies used to design and deliver these experiences also vary. In augmented reality, the technology projects virtual objects into a user's real-world environment. One popular example is the game Pokémon Go, which can be played on any smartphone. This type of game can be extremely costly to produce but has a relatively low cost to consumers. In contrast, virtual reality artificially creates the user environment. It is a more immersive experience, shutting out the real world visually and often audibly. Institutions are investing in the creation of virtual experiences through business partnerships and student-led teams. For instance, at Tennessee Tech, teams have created virtual experiences for students to drive a buggy on the moon and to visit WWII historical sites (<http://ttuicube.com/>). The costs of creating and experiencing virtual reality tend to be much higher than augmented reality, but technology companies are generally eager to support educational initiatives using their devices (Evans, 2018). There are also several inexpensive alternatives that educators can employ to engage learners in virtual reality using smartphone apps and a pair of cardboard or plastic goggles (Evans, 2018). Mixed reality environments are the most complex and least studied of these technologies. In mixed reality, digital objects appear real and allow the user to interact with them.

Cost and a high level of technical expertise pose major challenges to using augmented and virtual reality widely in education. A recent product purchased by Amazon may change the landscape of adoption of augmented and virtual reality in an all-in-one development platform that will allow for a drag-and-drop approach for augmented and virtual reality (Marvin, 2018). This new platform, Sumerian, may be a game changer in allowing augmented and virtual reality apps to truly integrate the physical and digital worlds using a heutagogical approach to support a model of self-determined learning.

Future of Jobs

Aoun (2017) discusses the need for a new discipline that he terms *humanics*. As president of Northeastern University, he calls for new literacies to be introduced as part of our work which allow students to experience new concepts in dealing with the changing landscape of higher education and work integration. Aoun posits that students will need data literacy, technological literacy, and human literacy, as well as significant experiential learning approaches within each literacy, to develop the depth of skills needed to be prepared for their futures. He also asserts that students must develop lifelong learning skills. This heutagogical approach to continuation of learning will prepare students for the needs of the societies in which they live today and in the future.

Michio Kaku, a theoretical physicist, believes the future jobs that will thrive are those that are nonrepetitive and those that require intellectual creativity and tasks that require thinking. Kaku's precepts (Crieghton, 2018) are shared by Aoun (2017) and are further defined in the literacies discussed above.

As Aoun (2017) and others have argued, the future jobs not easily adapted to the machine learned environment will be those that focus on communication and interpretation of human interactions. These types of jobs will underscore the need for a highly skilled workforce whose members are technologically and digitally literate and who excel in the abilities related to innovation.

Dyer, Gregersen, and Christensen (2011) advocate for considering the skills needed to innovate. The identified five skills needed to achieve innovation are the following:

1. *associational thinking*—identifying connections;
2. *questioning*—the passion for building learning through inquiry;
3. *observing*—learning through the experience of observing people, processes, and interactivity;
4. *networking*—building a group of “testers” to try new ideas and concepts; and
5. *experimenting*—the ability to try new things and enjoy the process of learning about a new approach.

Soft skills are needed today in the workforce and will continue to be needed in the future. It is assumed that soft skills are intuitive. However, the opposite seems to be true. In a Burning Glass Technologies report (2015), it was noted that one in three skills are considered baseline skills, even in the most technical career fields. These baseline skills include customer service, organizational skills, writing, communication, and basic technology skills.

Rainie and Anderson (2017) authored a Pew Research Report that states that the training ecosystem is evolving with a mix of innovation in all education formats. Learners will be required to cultivate these 21st-century skills in order to meet the needs of future employers. New credentialing systems will evolve to meet the changes in industry and employee needs. Today, we see this new approach to credentialing in micromaster's degrees and other innovative approaches to credential completion. As mentioned, blockchain technology may be used as a new way to document workforce and learner credentials. Work and jobs of the coming years will be launched by the entrepreneurial efforts of the workers. The workforce will continue to have both increases

in the need for highly skilled workers and decreases in employment opportunities that change based on the evolution of nontechnical job functions.

Building a Personalized (Professional) Learning Network

One key component of the future of jobs is that all students will find the need to develop a personalized learning network (PLN). The participants in these networks are both personal and professional learners. Individuals create PLNs using tools such as social media, communication events, collaboratories, and other technologies to connect with colleagues around the world.

Four characteristics of those using PLNs successfully include the following:

1. Adapting to the overall sense of being part of one's chosen field.
2. Demonstrating mindfulness by reaching out to find new and innovative ways to think about a problem or issue in their field.
3. Cultivating a sense of curiosity and an ability to think, learn, and share.
4. Building digital literacy skills that will provide the basis for collaboration across platforms and through a variety of tools.

By building on the theory of connectivism, the learner can adopt ways to creatively search out and participate in strong PLNs (Clifford, 2013). Becoming a participant in a PLN can be a powerful career booster. Use of the PLN can make a true difference in opportunities for professional growth and impact on the student's chosen field. It is the responsibility of the instructor to assist students with the ability and skills to begin to build and develop a PLN.

Conclusion

More people, including those with disabilities, are taking advantage of the flexibility online education affords. Technological advances allow many individuals to leverage the Internet to expand their knowledge and skills through higher education. Instructors and instructional designers are beginning to approach course development through UDL, thus intentionally building more inclusive learning environments that leverage technologies and student choice. A universally designed course affords students freedom and flexibility to engage in the teaching and learning process in a way that they determine is best for them.

Assessment of student learning, particularly in online environments, is being strengthened through the use of AI. In addition, AI tools support an instructor's ability to design and adapt learning paths to meet the uniqueness of each individual student's needs. This technology, with further development, could be used to increase student engagement and active, self-directed learning. Augmented, virtual, and mixed reality tools are also emerging as technologies useful for improved learner engagement. In augmented reality, virtual reality, and mixed realities, the lines between reality and computer-enhanced learning are blurred, creating unique learning experiences that could not be replicated in real life or are too costly or dangerous to do so. As technology continues to advance, the social and economic culture of our world is affected as well. Jobs, and the skills people need to be successful in their work, will likewise also be subject to rapid changes in the future. As educators, it is our job to prepare today's students for tomorrow's workplace. The best way to prepare them is to foster an ability to become lifelong, self-directed learners who can

successfully leverage technology and information resources and by building personal, professional learning networks.

At the end of the day, it isn't about what educators do, nor how we communicate our knowledge to our students: It is about what the students see us doing, what they have the opportunity to participate in, how they have actively participated in the *doing* of learning, and how they have seen us model the literacies needed to skillfully enable them to meet the needs of our future world. Learning is only successful when we fully assess the impact of our preparations and presentations on student outcomes. More applied and empirical research is needed in order for these emerging technologies to advance and become grounded within higher education. Further, students need the opportunity to actively participate in the *doing* of learning. Modeling the literacies needed to skillfully enable us to meet the needs of our future world through strong use of technologies in a heutagogical setting enables learning success.

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Introduction to Section II

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Editor, *Online Learning*

This issue of *Online Learning* contains four papers from our regular submission process. The studies in this section examine facilitation of productive discourse, uses of social media, interaction, and student success in online learning environments.

The initial paper in this section is “Scaffolding Progressive Online Discourse for Literary Knowledge Building” by Marc Nachowitz of Miami University, Ohio. This paper provides a lucid description of the design of online discussions that are likely to lead students to engage in progressive, literary discourse. Building on the work of Scardamalia and Berier, the author investigates the use of online discussion scaffolds—for example, sentence starters such as “I used to think...” and “But now I think...”—as ways to get students engaged in more reflective discussions in online settings. Using design-based research, analysis of discussion submissions indicates that direct instruction in progressive discourse in combination with classroom review of online discussion contributed to student learning. This study is helpful in advancing our understanding of knowledge building with a useful overview of the literature and approaches used in the field of computer-supported collaborative learning (CSCL).

The second paper in this section is “#DigPed Narratives in Education: Critical Perspectives on Power and Pedagogy” by Suzan Koseoglu of Goldsmiths, University of London, and Aras Bozkurt of Anadolu University and the University of South Africa. The authors’ goal was to understand how educational narratives grow and spread on social media. They used social network analysis and thematic content analysis to identify three main narratives. From their findings they identify pedagogic capacity as another conceptual lens through which to explore the growth and impact of critical narratives in education. This paper expands the theoretical toolbox for research in digital learning.

Next is “Increasing Undergraduate Success: A Randomized Controlled Trial of U-Pace Instruction” by Raymond Fleming, Laura Pedrick, Leah Stoiber, Sarah Kienzler, Ryan Fleming, and Diane Reddy of the University of Wisconsin, Milwaukee. This experimental research examines components of an instructional approach developed at the University of Wisconsin-Milwaukee designed to improve student success in undergraduate education courses in psychology. The approach combines mastery learning with “amplified assistance” (communication of high expectations, motivational support, and proactive instructor support). The study investigates the components individually and in combination and also evaluates a control condition with neither of the components. Results showed no significant difference in course grades within the U-Pace model. Significant differences did exist between students in “regular” face-to-face instruction and the combined U-Pace approach. The authors also found that students assigned to the combined condition did significantly better on a cumulative exam compared to the individual components. Finally, U-Pace instruction was found to be effective for both at-risk students and students not at risk. This is a well-designed and tightly controlled study of an effective

instructional intervention that begins to tease apart the active ingredients in a scalable approach to improving student outcomes.

The final paper in this section is “Increasing Interpersonal Interactions in an Online Course: Does Increased Instructor E-mail Activity and a Voluntary In-Person Meeting Time Facilitate Student Learning?” by Bianca Cung, Di Xu, and Sarah Eichhorn of the University of California, Irvine. In this paper the authors investigate the effects of increasing instructor interaction and voluntary face-to-face meetings on student performance in a precalculus course. Precalculus serves as a gateway course in higher education, and interventions that improve success can have broad impacts on the likelihood of degree completion, especially for academically weaker students. In the treatment group, students benefited from well-structured instructor e-mails that were sent on a regular basis to keep them on track and a voluntary weekly face-to-face meeting where students could ask questions about content that was unclear. Based on a sample of matched students, the authors conclude that these practices increase interactivity and result in better outcomes for students. Specifically, students in the higher interactivity condition scored four percentage points higher on their course final exam than students who did not receive this treatment. The higher level of interpersonal interaction also helped increase student final grades by almost half a grade. This is a useful study of a specific intervention that promises to improve online learner outcomes in a way that scales to larger contexts.

We are pleased to bring you these papers as well as the studies included in Section I. Please read, discuss, and share this work and consider contributing to the scholarly dialogue supporting the advancement of online education.

Scaffolding Progressive Online Discourse for Literary Knowledge Building

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Abstract

Drawing on research from online, knowledge-building, and discussion-based learning, this design-based experiment captures the instructional moves theorized to develop student capacity in progressive, literary discourse. The experiment employed Knowledge Forum and its unique capacity to scaffold student learning of progressive discourse that results in an explanatory model, theory, or literary interpretation. Analysis of student discussion posts within and between two iterative phases suggest that explicit instruction in progressive discourse, combined with regular classroom debriefings of online discussion, contributed to student mastery. Additionally, the use of sentence starters aligned with each Knowledge Forum scaffold for progressive discourse provided positive outcomes. Implications for using online, progressive, literary discourse scaffolds to inculcate disciplinary thinking and discussion appropriate to the secondary English/Language Arts class are discussed.

Keywords: online discussion, literature discussion, design-based experiment, progressive discourse

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Scaffolding Progressive Online Discourse for Literary Knowledge Building

Teaching online discourse around English/Language Arts (ELA) content is a twofold challenge. First, our nation's schools are failing to create highly literate, college- and career-ready adults with the literacy skills that qualify them for employment in the new, global knowledge economy (Carnegie Council on Advancing Adolescent Literacy, 2010). Consequently, calls for research investigating the kinds of literate acts 21st-century readers and thinkers need must encompass skills in thinking creatively, effectively communicating and collaborating with teams of people, and making innovative use of knowledge and information (Partnership for 21st Century Skills, 2008). Second, a body of research within the literacy education community has established positive correlations between discussion-based approaches to the teaching of literature and student understanding (Applebee, Langer, Nystrand, & Gamoran, 2003; Nystrand, 2006) justifying the creation and adaptation of an ELA Common Core Anchor Standard (CCSS) in speaking and

listening. Specifically, the standard calls for students who can “initiate and participate effectively in a range of collaborative discussions . . . building on others’ ideas and expressing their own clearly and persuasively . . . propel conversations by posing and responding to questions; and clarify, verify, or challenge ideas and conclusions” (Common Core State Standards Initiative, 2010). In short, the challenge for ELA educators and researchers is to establish valid practices for scaffolding students’ abilities to collaboratively construct knowledge through discussion and to prepare them to communicate and collaborate using 21st-century tools. However, there is a dearth of research investigating how these challenges might be met together. What is lacking, and what the present study addresses, is research investigating how instructional activities designed to develop 21st-century literacy skills might be integrated into conventional ELA instruction (Howell, Butler, & Reinking, 2017).

The author conducted a formative experiment with the goal of developing middle school students’ abilities to collaboratively direct and sustain effective discussions around literature content using online tools. Formative, design-based research seeks to understand and document how and why a designed intervention works *in practice* (Ford, McNally, & Ford, 2017). The present study sought pedagogical insight from employing digital discussion tools to scaffold students’ skills at collaborative knowledge construction to inform future research and instructional practices.

Review of Related Literature

Two strands of research informed the design of the study: *knowledge building* and *disciplinary literacy*. As the goal of this design-based experiment was developing students’ abilities to collaboratively direct and sustain effective literature discussions using online tools, a theoretical foundation from cognitive psychology, knowledge building, was selected for its close alignment with the stated goals. Bereiter’s *Knowledge and Mind for the Knowledge Age* (2002), an origin point for knowledge-building learning theories, called for pedagogical practices that encourage knowledge creation to produce students who deeply understand content. Knowledge-building learning trains students to generate knowledge through sustained collaboration and problem solving, leading to a shared understanding, or *knowledge product*. Producing knowledge products can only occur via an essential aspect of knowledge building: progressive discourse that emphasizes improvability of ideas (Bereiter, 2002). Typical classroom literary discussions often feature teacher and students mutually grappling with a problem of interpretation by focusing on textual evidence. These kinds of literary discussions “do not generate progress toward the solution of shared problems of understanding” (Scardamalia & Bereiter, 2006, p. 102). Teachers may pose open-ended questions and invite students to share their interpretations of an author’s craft, but there is one essential aspect missing for progressive *literary* discourse: the purpose of the discourse is to *get* somewhere. Thus, progressive literary discourse should result in a final knowledge product: a shared, deep interpretation of a text justified by student analysis and synthesis of literary knowledge.

The second theoretical perspective informing this study, disciplinary literacy, required consideration of the content area or discourse community in which the online discussions took place. Disciplines are distinguished by discourses (Luke, 2001; O’Brien, Moje, & Stewart, 2001), and recent scholarship in disciplinary literacy recognizes students’ need for learning the knowledge of texts and literate practices as well as the inquiry practices/strategies of reasoning

required in each content area (Goldman et al., 2016; Moje, Young, Readence, & Moore, 2000). As Moje (2008) noted, “Producing knowledge in a discipline requires fluency in making and interrogating knowledge claims, which in turn require fluency in a wide range of ways of constructing and communicating knowledge” (p. 99). Reading, writing, and discussing literary texts requires cognitive processes, skills, dispositions, and funds of knowledge not engaged when reading other texts (Lee, 2007; Miall & Kuiken, 1999; Moje et al., 2000; Wineberg, 1991).

Noting the importance of content and rhetorical processes, Goldman et al.’s (2016) conceptual framework for disciplinary literacy captures the unique norms, conventions, and ways of discussing knowledge within a discipline. The authors describe the discourse and reasoning skills students need to interpret literary texts and construct oral and written arguments that communicate their interpretations. For example, expert, literary readers attend to plot and character, language and structure of the text, knowledge of other texts, and awareness of the author’s craft, such as the use of symbolism or tone as they affect textual understanding. Literary discussion, like argumentation in the other disciplines, involves supporting claims with evidence, supporting reasoning with credible warrants, and responding to counterclaims (Toulmin, 2003). However, the discourse of literary discussion also accepts personal beliefs and life experience as valid claims. Literary discussion acknowledges texts as a means to understand the nature of human experience, that texts may have ambiguous meanings, and, thus, that multiple interpretations of a text are valid because the discourse and reasoning utilized in literary analysis and discussion accepts the personal beliefs and life experiences of the reader as acceptable warrants (Lee, Goldman, Levine, & Magliano, 2016). Thus, the present study designed an intervention using online discussion encompassing the aforementioned characteristics of how knowledge is discussed, constructed, challenged, and revised within the literature classroom.

The Intervention and Its Justification

Improving Online Discourse as a Pedagogical Goal

Online discussion forums provide a unique opportunity to understand and develop pedagogies that might enable improved collaboration and discussion around content. Researchers believe that asynchronous online discussion forums are potentially ideal environments for the social construction of knowledge (Gao, 2014), providing students and teachers with a space to engage in discourse around content and construct knowledge (Chen, deNoyelles, Patton, & Zydney, 2017). Online courses that promote high levels of collaboration facilitate increased value in the co-construction of knowledge (Wicks et al., 2015). Nonetheless, online discussions often fall short of this objective (Rourke & Kanuka, 2009).

Engaging students in online learning requires exploring the nature and the quality of digital interactions that foster connections with other students and the instructors “while developing strong disciplinary knowledge and multidisciplinary skills” (Redmond, Heffernan, Abawi, Brown, & Henderson, 2018, p. 199). Online learning that nurtures social, cognitive, behavioral, collaborative, and emotional engagement may improve the quality of online learning (Redmond et al., 2018). Moreover, while elements such as learner-to-instructor engagement strategies are highly valued by students (Martin & Bolliger, 2018), MOOC courses can improve engagement by implementing discussion prompts that foster interactions about deep meaning of concepts covered in the course (Bonafini, Chae, Park, & Jablokow, 2017). These studies provide a useful framework for improving student engagement in practice and research, but they do not posit specific

instructional moves. Thus, the present study examines one method for improving student engagement by employing a technique for propelling discussions with structured discourse.

To improve the quality of online discussions, one strand of scholarship has investigated the use of structured discourse. For decades, sentence frames have been employed to facilitate effective face-to-face discussions and collaborative writing (Adler & Rougle, 2005). Essentially, sentence frames provide language to focus student contributions and advance discussion. Students are presented, for example, with a menu of phrases to begin the first sentence of a discussion, such as, “at first I thought, but now I think,” to give them the language that shapes reflective thinking. Also referred to as *note starters*, these sentence frames are a form of scaffolding intended to deepen student thinking (Nussbaum, Hartley, Sinatra, Reynolds, & Bendixen, 2004). The first application of note starters in online learning was conducted by Scardamalia and Bereiter (1991) who adopted the practice for online discussions, concluding that the practice supported high-level questions, elaborated explanations, and improved student understanding.

Substantial scholarship in the field of online learning has examined ways to teach students strategies for improving digital discussion. Noting the challenges of online discussions, Hara et al. (2000) designed a study using *starters*, who initiated weekly discussions around assigned readings, and *wrappers*, whose task was to summarize the discussions. The authors suggest that defined roles and discussion tasks improved the length, cognitive depth, and discussion posts embedded with peer references. Nussbaum et al. (2004) combined research on argumentation to design a framework for facilitating students’ online discussion skills by providing them with note starters to encourage counterargumentation. For example, their note starters included the phrases “my argument is,” “I need to understand,” and “on the opposite side.” The study suggested note starters could be useful for students with low degrees of curiosity and appeared to encourage students to consider other points of view during online discussions. However, the study only studied starters as a method for facilitating student argument; it did not examine the use of note starters as a means for generating ideas around content. Jonassen and Kim (2010) noted the potential of note starters, what they refer to as *preclassifying messages* to support student learning of the rhetorical structure of argumentation in online forums. Chen and Hun (2002) theorized that if the goal of online learning is to facilitate shared knowledge construction, then note starters, such as those used by Knowledge Forum, are well suited to developing student skills in collaborative discourse. More recently, studies investigating the role of computer-embedded supports, such as note starters, sentence frames, or scaffolds, find them necessary to enhance student learning and collaborative support (Morris et al., 2010; Ng, Cheung, & Hew, 2010; Noroozi, Weinberger, Biemans, Mulder, & Chizari, 2013). However, none of the studies cited here examine sentence frames as a tool for developing students’ abilities with progressive, literary discourse

Developing Progressive, Literary Discussions With Online Tools as a Pedagogical Goal

To design an intervention directed toward developing students’ abilities to self-direct and sustain online discourse around literary content, it was necessary to investigate the qualities of effective literature discussions established in the research base, paying particular attention to the skills and dispositions educators emphasize. In collaboration with the classroom teacher, I theorized that such teacher-directed discussion practices could be transferred and taught to the students using online digital tools (i.e., sentence frames or note starters) to inform the design of the intervention. Thus, the following review of dialogically organized instruction in the ELA classroom provides insights into the intervention’s design.

For decades, empirical studies in the literacy field have examined the role discussion plays in developing reading, writing, and reasoning appropriate to ELA classrooms (see, for example Applebee et al., 2003; Langer, 1995). The presence of discussion in the literature classroom does not necessarily equate with improved student learning; it is the quality of the discussions that foster reasoning appropriate to literary discussions. Discourse focusing on the student as meaning maker “requires elaboration of the learner’s, not the teacher’s, interpretive framework” (Nystrand, Gamoran, Kachur, & Prendergast, 1997, p. 20). Classrooms in which students engage in substantive, ongoing dialogue are characterized by the presence of multiple perspectives, the development and improvement of understandings over time, student questioning, and the practice of building on the comments of other students (Juzwik, Nystrand, Kelly, & Sherry, 2008; Langer, 1995; Nystrand, Wu, Gamoran, Zeiser, & Long, 2003). The effectiveness of instructional discourse is “a matter of the quality of teacher-student interactions and the extent to which students are assigned challenging and serious epistemic roles requiring them to think, interpret, and generate new understandings” (Nystrand et al., 1997, p. 7). The most effective ELA dialogue, according to Nystrand et al., required students to think and not merely report someone else’s thinking, and this occurred most frequently when teachers asked open-ended questions and challenged students to extend and justify their interpretations.

Thus, I decided to transfer the epistemic roles and teacher-uptake discourse moves established in the literature when designing the intervention. Because the literature establishes the importance of discourse elaborating and building on the learner’s interpretive framework, not the teacher’s, discussions should begin wherever the students wanted to begin. They should be taught how to start discussion with questions, wonderings, confusions, or anything that they noticed and wanted to discuss. Furthermore, research on effective literary discourse establishes the critical role of teacher uptake, when teachers incorporate student responses to extend and justify students’ thinking, into the questions they pose. These are key factors in discussion-based classrooms and are equated with improved literacy skills (Nystrand, 2006; Nystrand, Gamoran, & Carbonaro, 1998). Thus, if these were the effective teacher moves in rich, dialogically organized instruction, a self-directed and sustained student discourse might mimic these approaches. The intervention should explicitly model and scaffold students’ skills and dispositions toward extending, challenging, justifying, and unifying discourse around literature—all discrete uptake moves made by teachers in classrooms identified as dialogically rich environments. Scaffolds and sentence frames built into a digital discussion board, I theorized, could model and reinforce students’ application of typical uptake moves.

Employing Knowledge Forum to Achieve Pedagogical Goals

In studies of knowledge-building classrooms, a computer-supported learning environment, Knowledge Forum, is the principal environment in which work with ideas takes place. It is where ideas are set forth, discussed, revised, organized, and combined (Bereiter & Scardamalia, 2003). Knowledge Forum is a networked, community knowledge space in which participants contribute notes that may be theories, ideas, questions, references, connections, or multimedia. When contributing a note, participants can *co-author*, *build on*, or *annotate* notes written by other members of the community as well as create *keywords* “and *rise-above* notes to summarize, distill, and advance their discussions” (Zhang, Scardamalia, Lamon, Messina, & Reeve, 2006, p. 123).

Knowledge Forum’s ability to structure discipline-specific ways to generate explanatory theories and revise them over time is especially salient to this study. When posting discussion notes, participants must select from a menu of *scaffolds* to facilitate progressive discourse—similar

to sentence frames or note starters. For example, when a student wishes to initiate a discussion topic or build on others' ideas, a pop-up window appears, and students must select from a menu of scaffold choices framing their post. These scaffolds initiate the participant's note composition by providing guidance with categories such as "my theory," "I need to understand," "new information," "a better theory," and "putting our knowledge together." Scaffolds are a way to inculcate the structure of discourse in discipline-specific ways. In essence, students internalize the epistemology of the discipline by participating in conversations justified by discipline-appropriate ways of constructing, revising, and thinking about knowledge in the domain.

There is growing support in the literature establishing the effectiveness of Knowledge Forum and knowledge-creating communities for improving student learning in math, science, and social studies (Bielaczyc & Collins, 2006; Messina & Reeve, 2006; Moss & Beatty, 2006; Niu & Aalst, 2009; Zhang et al., 2006). However, only a few studies investigate knowledge-building learning on literacy skills. Elementary students engaging in knowledge building have shown significant gains in literacy even without any special attention to it (Scardamalia, Bereiter, Burtis, Calhoun, & Smith Lea, 1992), particularly improvement in discourse, reading, vocabulary growth, and reading to create knowledge (Lamon, Chan, Scardamalia, Burtis, & Brett, 1993; Scardamalia, 2002; Sun, Zhang, & Scardamalia, 2010; Zhang & Sun, 2011). Only one study to date has examined knowledge-building learning in the secondary ELA classroom. Lamon (2005) investigated the use of Knowledge Forum as a tool for improving Grade 9 students' literacy skills, finding a positive correlation between database activity and final grades. However, the unpublished study did not elucidate knowledge-building learning in the ELA classroom beyond suggesting how teachers could generate problems of understanding to drive curricula.

The knowledge building theory of learning, facilitated by Knowledge Forum's ability to train students in mastering a progressive, literary discourse was selected for this study to improve the quality of online discussions. Knowledge Forum's scaffolds focus discussion in a way that classroom discussions cannot; it requires students to build on, advance, challenge, and justify ongoing conversations. The collaborative, knowledge-building nature of the software environment provides ways for participants to see patterns, integrate ideas, and visually map the development of ideas in ways that chats, dialogic journals, classroom discussions, bulletin boards, or threaded discussions cannot. The goal of using Knowledge Forum is to use technology in a way that allows for progressive discourse and the crossing and recrossing of understandings (Spiro, Coulson, Feitovich, & Anderson, 1994) so that students live an enhanced literary experience with practical application (Scardamalia, 2003). Technology that goes beyond typical discussion formats and can facilitate the use of scaffolds to foster progressive discourse provides both an opportunity to add to the literature concerning online, dialogic, and knowledge-building learning. Moreover, understanding how students learn to apply Knowledge Forum's scaffolds in literary discussions will contribute to the research base regarding sentence frames as a means to improve online discussions.

Research is needed examining how online learning can promote high levels of collaboration leading to the co-construction of knowledge. As online discussions fall short of this objective (Rourke & Kanuka, 2009), the present study hopes to contribute to the literature on promoting effective, digital discussions particularly in the literacy field. Furthermore, research is needed to provide insights into the cognitive and social practices required for students to manage, understand, apply, and create knowledge (Goldman & Scardamalia, 2013) in ELA. As design-

based experiments are interested in how and why a designed intervention works in classroom practice, the research question guiding the present study investigated the following:

- How can digital discussion tools be integrated into conventional ELA instruction to help students learn the reasoning and rhetorical skills and dispositions appropriate to progressive, literary discourse?

Methods

Research Design

The present study employed a mixed methods design within the design-based research (DBR) paradigm. Since progressive, literary discourse and its development over time was an essential factor in this research, a methodology had to be selected to track environmental factors and student learning as their discussion, reasoning, and interpretation skills were evolving. The objective of DBR is to understand an emerging theory of educational design, often a close study of a single learning environment, as it passes through multiple iterations to reach a desired goal (Barab, 2006; Gravemeijer & Cobb, 2006; Parker et al., 2013). Unlike experimental or quasi-experimental research methodologies where data is analyzed at the end of the experiment, design-based research gathers and analyzes data in regular, iterative cycles over the entire course of the experiment, wherein data are analyzed, and suggestions to improve the instructional theory are implemented, followed by a new cycle of data collection and analysis, until the goal is reached (Botha, van der Westhuizen, & De Swardt, 2005; Collins, Joseph, & Bielaczyc, 2004; Reinking & Bradley, 2004). Data were gathered and analyzed as they informed iterative modifications of the intervention guided by questions such as the following: What factors enhance or inhibit progress toward the pedagogical goal? How can the intervention be modified in light of those factors? (Colwell, Hunt-Barron, & Reinking, 2013; Howell et al., 2017).

The Participants

As DBR methodology can provide an overwhelming amount of data for daily, weekly, and monthly analysis, it has been recommended to limit the experiment to one class (Reinking & Bradley, 2008). A call for participants was distributed to schools and teachers within the geographic region situated around a large city in upstate New York. The participants selected for this study, members of a single sixth grade ELA class of 26 students, were chosen for their rich academic and ethnic diversity. Approximately one third of the class was ethnically diverse, and one quarter of the students came from homes where a language other than English was spoken. Additionally, four students of the 26 were identified as requiring instructional support via Individualized Education Plans. To protect the privacy of the teachers and students engaging in this study, signed consent forms from students and their parent were obtained. All data recorded and reported here use pseudonyms to protect participant privacy. In design-based research, the classroom teacher is considered a co-investigator. Thus, data were reviewed and decisions to implement and revise the intervention and delivery of instruction were made with the full participation of the teacher.

The Intervention

The intervention aligned principles of knowledge-building learning with the regularly prescribed curriculum. No changes were made to *what* students learned. Rather, design principles

solely emphasized *how* students would meet learning objectives. The intervention focused on establishing key components of knowledge-building learning (Scardamalia, 2002):

- *Improvable ideas*: Learning activities and teacher-student interactions established that all ideas regarding literary theories were improvable and that no knowledge—even that from authoritative sources—was finite.
- *Rise above thinking*: Learning activities focused on scaffolding students’ abilities to develop emerging understandings and encouraging them to build on and extend their own and other students’ ideas.
- *Progressive discourse*: Students practiced adding to, justifying, and challenging literary interpretations in classroom and Knowledge Forum discussions in which the progression of ideas, idea diversity, and building on others’ ideas became visible and extended beyond one class or one learning activity.

During the semester-long intervention, key changes were made to weekly instruction. First, Knowledge Forum sessions would take place twice weekly in the school’s computer lab to assist students in mastering the software environment’s intricacies. Each Knowledge Forum session would be debriefed the following day for the express purpose of providing instructional feedback and guided practice in progressive discourse. For example, a discussion thread that posed interesting questions but was not built on by students would be displayed in class, and the teacher would model ways to add to, justify, challenge, or unify the discussion, and students would practice applying these dialogic skills.

Crafting effective scaffolds, or sentence starters, to focus Knowledge Forum discussion posts toward a progressive, literary discourse was an essential factor affecting the research design. Prior to the intervention reported here, a pilot study applied the theory-building, progressive discourse scaffolds programmed into Knowledge Forum and they were deemed inadequate. Analyses of students’ Knowledge Forum discussions during and after the pilot study revealed a high percentage of students initiating discussions but an extremely low percentage of posts that extended and built on other students’ posts. It was theorized that this outcome might be a result of Knowledge Forum’s discussion scaffolds not being appropriate for knowledge-building, *literary* discourse. Thus, for the intervention, new discussion scaffolds were designed to mimic the kinds of uptake ELA teachers demonstrate in effective dialogic classrooms (Nystrand, 2006; Nystrand et al., 2003). The old and new scaffolds applied in this intervention are provided in Table 1.

Table 1

Discussion Scaffolds for Knowledge Forum

Knowledge Forum’s <i>theory-building discourse</i> scaffolds applied during pilot study	<i>Literary discourse</i> scaffolds applied during intervention
My theory	I want to talk about
I need to understand	I have a question
This theory cannot explain	Challenging ideas
A better theory	Justifying ideas
Putting our knowledge together	Extending ideas
	The big picture

The new scaffolds were designed to assist students in entering and extending online discussions in ways typical of ELA classrooms. The author theorized that these scaffolds would assist students in constructive talk about text as well as highlight the importance of justifying literary interpretations with evidence through the *challenging*, *justifying*, and *extending* scaffolds. Thus, the intervention focused on teaching students progressive discourse that would enable them to create literary knowledge.

As design-based research allows the investigators to tweak the intervention to bring students closer to the educational goal, data were debriefed, by the author and the classroom teacher, in iterative cycles to illuminate the instructional changes affecting learning outcomes. After 10 weeks (Phase 1) it was theorized that changes to the intervention would bring students closer to the research goal. During Phase 2 students were provided sentence starters to help them find the language aligned with specific Knowledge Forum discussion scaffolds (see Appendix A). Students were required to access these sentence starters during all computer sessions and face-to-face discussions. Second, in order to propel students to synthesize patterns in the text, as well as making connections to the world beyond the text, a new Knowledge Forum discussion scaffold, *the big picture*, was introduced and explicit instruction offered to support student mastery of this thinking and discussion technique. These phases and their rationale will be discussed further in the results section.

Student Activity Measures: Knowledge Forum Usage

To track student growth toward the intervention's pedagogical goal, student mastery of progressive, literary discourse, data were analyzed after each phase of the design-based experiment. Focusing on Knowledge Forum's performance indicators (e.g., use of scaffold supports, discussion tree sizes, notes read, notes built on) provided the primary source of data determining the extent to which students were moving closer to, or away from, the pedagogical goal. Thus, tracking student performance in real time provided necessary data informing the study's research question: How can digital discussion tools be integrated into conventional ELA instruction to help students construct effective, progressive, literary discourse? Teacher interviews, lesson plans, student artifacts, and researcher field notes were used to triangulate quantitative and qualitative analyses in relationship to iterative phases of the design, noting especially instructional changes to the intervention. The learning outcomes presented in the following sections employ quantitative measures from Knowledge Forum and qualitative analyses of student discussions. Interview data, lesson plans, and other artifacts are not discussed explicitly, yet they were used to situate the data within the context of the intervention and student responses as they changed over time.

Quantitative measures were utilized to examine student selection of Knowledge Forum scaffolds to assess the extent to which students were applying the elements of a progressive, knowledge-building discourse appropriate for literary knowledge building. Descriptive statistics of this variable by iterative phase were examined to track the effects of changes to the instructional intervention. Correlational analyses (chi-square) were performed to examine the use of student scaffold supports to aid the understanding of changes to the instructional intervention, across phases, and between Phases 1 and 2. Additionally, Knowledge Forum provides analytic tools to track individual and whole-class discussion contributions. These quantitative measures examining discussion tree sizes and links between student posts were used to understand student application and growth of progressive discourse measures.

To determine the extent to which students were actually engaged in progressive, literary discourse, discussion trees were analyzed qualitatively, specifically for evidence of students grappling with problems of understanding a text, providing explanatory theories, challenging and verifying such theories, and resolving issues. In essence, progressive discourse requires that student-initiated discussion events should go somewhere, deeper into the text. All threads were analyzed for evidence that students were engaged in solving problems of understanding the text solely through collaboration supported by Knowledge Forum. Threads were also analyzed for evidence of thinking, reasoning, and discussion skills and dispositions appropriate for the literature classroom as discussed in the theoretical and literature review sections of this study. From the perspective of thinking and discussion skills appropriate to literary reasoning, (see for example, Goldman et al., 2016; Lee et al., 2016), discussion threads were examined for students' noticing and noting things on their own, asking questions, being open to multiple interpretations, and either resolving questions, citing several potential answers, or accepting ambiguity.

Results

Commensurate with recent scholarship in formative and design-based experiments (see, for example, Colwell et al., 2013; Howell et al., 2017), results are presented first as retrospective analysis, evaluating overall student progress made toward accomplishing the pedagogical goal. Afterward, I discuss the enhancing factors and modifications made during the intervention and what the data suggest for modifying the intervention for future iterations.

Knowledge Forum Activity Measures

To address the research question—How can digital discussion tools be integrated into conventional ELA instruction to help students construct effective, progressive, literary discourse?—students' use of Knowledge Forum scaffold supports and examination of discussion tree size and quantity were examined to determine whether students were applying a progressive, knowledge-building discourse. Table 2 presents an overview from Knowledge Forum's built-in, analytic tools and provides a snapshot of strictly quantitative measures of students' contributions and engagement in progressive discourse.

Table 2

Knowledge Forum Measures

	Phase 1 (10 weeks)	Phase 2 (10 weeks)
Total notes contributed	240	366
Percentage of authors' notes that are linked	48%	65%
Total number of discussion trees	40	80
Percentage of discussion trees identified as small discussion trees (2–5 notes)	88%	85%
Percentage of discussion trees identified as medium discussion trees (6–20 notes)	10%	14%
Percentage of discussion trees identified as large discussion trees (21–40 notes)	0%	1%
Percentage of discussion trees identified as very large discussion trees (more than 40 notes)	2%	0%

There are several Knowledge Forum measures that indicate the quantity, if not the quality, of students' participation in progressive discourse. For literary discussion to move forward, to dig deeper into literary analysis, students must show evidence of reading each other's posts and building on them. The category *percentage of authors' notes that are linked* indicates the percentage of all notes that are connected through building on and extending earlier posts. This statistic increased from 48% in Phase 1 to 65% in Phase 2, indicating that the overall, ongoing discourse around literature became less disjointed and more connected.

The snapshot of the size of discussion trees and their corresponding percentages provides another measurement of students' participation in progressive discourse. Discussion trees are threads of related student posts, originating with one note and branching off as students identify and narrow subsequent discussions on particular ideas. As discourse becomes more complex, discussion trees should become longer, and the occurrence of longer discussion trees should become more frequent. There is a fairly consistent pattern here of discussion trees of fewer than five notes. The very large discussion tree from Phase 1 is best understood as an anomaly, as this tree was created by the teacher and was designed to initiate students into online discourse following their reading and study of memoir as a genre. In this light the 1% of discussion trees categorized as large discussion threads (21–40 notes) during Phase 2 should be seen as positive growth as the thread was entirely student generated. The data presented in Table 2 indicate that over the course of the intervention students grew in their use of progressive discourse in that they read and built on others' posts rather than concurrent posts of students' literary thoughts.

The unique feature of Knowledge Forum is its requirement that students select scaffolds to focus their discussion contributions. To ensure students are learning a progressive discourse, students are required to select from a drop-down menu of choices as they initiate, challenge, justify, revise, or unify their emerging literary understandings. Table 3 describes student selection of scaffold supports between and across experimental phases.

Table 3
Student Selection of Knowledge Forum Scaffold Supports

Scaffold selected	Phase 1 (10 weeks)	Phase 2 (10 weeks)	Total percentage across cycles
Not provided	23%	13%	16%
I want to talk about	35%	27%	29%
I have a question	6%	9%	8%
Challenging ideas	13%	11%	11%
Justifying ideas	3%	12%	10%
Expanding ideas	18%	24%	23%
The big picture	2%	4%	3%
			100%

N = 506 Knowledge Forum discussion posts

Progressive discourse is essential to knowledge-building learning, and *student use of scaffold supports* is one way to determine whether students are learning to engage in and apply the conventions of advancing literary discussions toward a knowledge product. Phase 2 showed substantial gains from Phase 1 in student selection of *justifying* (from 3% to 12%) and *expanding* (from 18% to 24%) progressive discourse scaffolds. The decrease during Phase 2 in the use of *I want to talk about* scaffold (from 35% to 27%) evidences students' cohesion and extension of other students' literary interpretations. That is, students demonstrated improvement in building on other students' literary interpretations rather than initiating numerous discussion threads. Across the entire intervention, 37% of discussion posts were written by students who initiated topics and raised questions about the text, and 44% of all discussion posts challenged, extended, and justified the formation of textual understanding over time. Students were engaged in *rise above* thinking by reading each other's posts and extending, justifying, and challenging others' ideas as they read the text.

As there were significant changes to the intervention implemented at the outset of Phase 2, it is important to measure the effects of instructional changes on student outcomes. To determine any influences of the instructional changes between research phases, chi-square tests were conducted to examine whether the proportions of posts in student selection of scaffold supports varied from Phase 1 to Phase 2. The *Cramer's V* effect size (.204) represents a moderate association for scaffold selected per Rea and Parker's (1992) interpretative guidelines. These results suggest that the proportions of students' Knowledge Forum posts at the different scaffold did in fact differ between Phase 1 and Phase 2 of the study.

Attributing changes to the instructional intervention accounts for some variability in student use of scaffold supports. The twice-weekly debriefings of Knowledge Forum sessions, aligned with the teacher's explicit instruction in mastering a progressive literary discourse, showed improvement of student application of scaffold supports over the entire intervention. However, providing students with sentence starters to shape the kinds of thinking and writing associated with specific progressive discourse moves was the most significant change to the intervention between Phases 1 and 2. During Phase 2, students were required to access and refer to the sentence starters during every Knowledge Forum session as well as during face-to-face classroom discussions. While it is possible to attribute student growth in application of advanced knowledge building, discourse scaffolds to mastery over time, it is more likely that explicit instruction in progressive discourse, aided by the sentence starters, played a significant role in explaining the variability between Phases 1 and 2.

Student Growth Toward *Literary Reasoning and Discussion*

The purpose of this design-based experiment was to understand how instructional changes might foster student application of a progressive literary discourse. Data tracking the extent to which students reached the goal of online discussions appropriate to how knowledge is or is not constructed in the ELA discipline provides depth to an understanding of the study's instructional outcomes. All Knowledge Forum discussion trees were examined for the *quality* of students' progressive literary discourse. As the quantitative findings suggest, students were applying advanced scaffold supports to justify, challenge, and build on other students' posts. However, qualitative analyses investigating the nature of these discussion threads were required to see the extent to which students were engaging in discussion around literature that went somewhere, that resulted in literary interpretations or socially constructed, shared understandings of questions, issues, themes, or concerns noted by readers. Thus, discussion threads were examined for students'

noticing and noting things on their own, asking questions, being open to multiple interpretations, and either resolving questions, citing several potential answers, or accepting ambiguity as appropriate for literary reasoning (see, for example, Goldman et al., 2016; Lee et al., 2016).

In this section, I present illustrative examples of students' enactment of progressive, literary discourse. These discussion trees are presented not because they are exceptional, but rather because they were *typical* of the high-quality, progressive discourse students achieved throughout their Knowledge Forum discussions. While there were certainly discussion trees that fizzled out or did not go beyond noticing and noting items or asking questions interesting to the student, those were very few. For clarity and conciseness, both examples encompass discussion of Sharon Draper's young adult novel *Out of My Mind* (2010).

During Phase 2, student discussion threads evidenced dispositions to literary conventions and applications of reasoning and argumentation indicative of the deepest levels of literary understanding. It took many weeks to establish a culture of *idea diversity* in which all student ideas are valued and treated as worthy of further discussion, but on this particular day, after several weeks of reading the novel, one student decided the image on the cover held some significance and wanted to bring his theory to the class. Students' Knowledge Forum posts are presented with the scaffold they selected in italics and without mechanical corrections to preserve their original voice:

Azim (I want to talk about): I think that the fish bowl on the cover represents Melody's head. The fish is trapped in the bowl, kind of like how Melody's words are trapped in her head. The fish is constantly swirling around the bowl, kind of like Melody's words swirling around her head. One day when the fish really can't take it anymore, he gets out, and I think that when Melody can't take it anymore, the words will come out. What do you think?

Ashlyn (I have a question): I agree with what you think the cover of the book means. I wonder what will happen if one day Melody has a major tornado explosion and she won't stop?!?!?!?!?!?!?!?

Ashlynn is taking up Azim's theory about what the cover might represent. Azim elaborates on his tentative suggestion, and Ashlyn ponders the implication of Azim's theory and wonders ahead to the remaining, unread portions of the book to see whether his theory might affect her reading predictions.

Lindsey (The big picture): I think that you are correct, but since the fish just decided he couldn't take it anymore and jumped out, will Melody really explode? And not be able to take it anymore.

Cynthia (Expanding ideas): I agree with you. I also wonder if the fish bowl is a warning for something that might happen on later in the book. Maybe that something doesn't have to be Melody that has to explode, maybe it's Mrs. V or Melody's dad or mom. The Dad could explode from all of his stress, or maybe Mrs. V has a dramatic character change, and explodes in one way. Or it might be Mr. Dimming that explodes. Does anybody else think this?

Notice here how Cynthia and Lindsey are picking up Azim's theory and using it to rise above thinking to add to and suggest alternative theories. This predisposition toward multiple possibilities is indicative of literary reasoning, as the discussants, using tentative language, suggest further

implications of Azim's reading on predicting the remainder of the plot and character developments.

Azim (*Justifying ideas*): Wow, you made a great point. I should've thought of that. Maybe it's not Melody that explodes, it could be someone else! Great point Christine

Brian (*Expanding ideas*): It could be it might also be Melody hase such a big tornato explosions is so bad Melody could have a heart attack from all the strees on her heart ang the ffish that resembols the beat of the heart giving up and jumping out "stopping"

Students were not asked to look for particular literary elements, such as symbols, but as this thread demonstrates, they brought them up on many occasions. Azim wanted to talk about the cover that he felt was important and suggested a theory for what a fish jumping out of the bowl might represent. Ashlyn asks what Azim's theory might mean for predicting future novel events, and Lindsey applies Azim's theory toward a big picture understanding of how the symbol might help her better understand the main character. Cynthia expands and takes up Azim's theory and offers tentative suggestions about the implications of his theory, using language of "maybe" and "it might mean" to expand on the emerging theory of symbolism by suggesting the fish might represent other characters. Brian zeroes in on the language suggested in Azim's follow-up note and suggests the tornado explosions might be a metaphor for heart stoppage.

This thread demonstrates students engaging in progressive, knowledge-building discourse and reasoning specific to the ways literary knowledge is constructed. An interpretation was put forth, students questioned, expanded, and justified the theory, applying constructive argumentation moves to propel the discourse forward, and as they did, a more fleshed-out idea of what the fish symbol might represent was created. This *rise above* thinking, aligned with constructive literary argumentation, is most likely attributable to the intervention's emphases on idea diversity and knowledge-building discourse, which were explicitly introduced and practiced through Knowledge Forum's discourse scaffolds supported by sentence starters.

Even though students were not explicitly instructed to look for literary elements and author's craft by the teacher, the discussion threads reveal that they noticed them anyway because they seemed important to the students as they were reading. For example, the following discussion took place following the book's completion toward the end of Phase 2:

Malik (*I have a question*): I wonder why the author ended the book this way. She ended it the same way it begun. Why did she end it with her thinking? Maybe it kind of refreshes back to when Melody couldn't talk, and she could only think, and keep things stuck in her mind. Melody couldn't talk, but now she is capable in a way of verbalizing The author also ended it with a ... so i wonder if there will be a sequel. Melody has been through alot, but I wonder what would've happened if Melody it wasn't from Melodys point of view? What do you think?

Amelia (*Justifying ideas*): i think she did this to show Melody reflecting back on her self then, what she used to be and what she is now.

Lindsey (*Expanding ideas*): I think that it would have been a whole diffrent story if it wasnt from melodys point of view because most of the book is her thinking. I also wonder if there will be a sequel. And you said that in the begining she could only think but now she can talk but she said in the end that she is eleven and she has never spoken 1 single word.

Malik (*Expanding ideas*): If the Point of view was in Claire or Mollys view, or even Rose, or Dad or Mom, what would they think? Do you have any ideas? The whole story would be a whole new story, what do you think?

Faraj (*Expanding ideas*): I think that a really interesting point of view would be Mr. Dimming's. I wonder what he would be thinking when he had to leave Melody and when Melody confronted him and the quiz team. How would the author explain his discomfort and how sorry he was?

Iris (*Expanding ideas*): I agree with Lindsey. I think the story would be way different. It might be similar to Melody's point of view but characters think differently. They see things happen in a different way. I think it would be a whole lot different.

Danielle (*I want to talk about*): I think it ended the same way it begun because Melody's thinking is the most important part in the story because without her thinking the story would be SOOO different and nobody would understand what's she's going through, and how her life is because if it was from Claire's point of view, imagine how different that would be! Yes if it wasn't from Melody's point of view I specifically wonder what it would be from Rose or Claire because I wonder what Rose was thinking when she didn't call Melody at the airport and also with Claire I wonder what she's thinking when she makes fun of Melody.

Students weighed alternative theories on point of view and how that affected overall textual interpretations. Here, students engaged in synthesizing the elements of author's craft (ending the text identically to the beginning) and point of view to see how these discrete literary elements, if changed, might affect possible, textual interpretations. Students were never told to examine point of view or the novel's structure. They were given the freedom to explore topics and questions they generated, and they raised these issues because they noticed that they might be important. This kind of literary talk, analyzing and synthesizing literary elements into a cohesive interpretation is indicative of progressive, literary discourse. In other discussion threads, students brought up theme, symbolism, irony, and characterization, carefully weighing evidence to support multiple interpretations.

There were no significant patterns or differences in the qualitative analyses of the discussion threads between Phases 1 and 2. Again, because students were applying Knowledge Forum's progressive, literary discourse scaffolds to their digital conversations from the very beginning, the qualitative analyses of discussion threads across phases demonstrate consistent student application of constructive argumentation, literary reasoning, and progressive discourse throughout the intervention. While there were discussion threads that did not progress deeper into the text—or fizzled out over time—they were in the minority.

Enhancing Factors and Modifications

In this section, I describe two enhancing factors that influenced the formative modifications to the intervention, bringing the students closer to the pedagogical goal. As the study's research question investigated how digital tools can be integrated into conventional ELA instruction to help students to construct effective, literary discourse, I discuss two instructional modifications that springboarded student growth between and across phases.

Synchronous debriefings of asynchronous discussion. During Phase 1 of the study, data analyses revealed that while students were initiating discussions and asking questions, there was

inadequate use of the advanced scaffolds that would guide students to dig deeper into the text, more fully articulating their interpretations, and challenge, justify and extend emerging literary theories. Thus, it was decided to implement a significant change to the intervention for Phase 2: increasing the frequency (from weekly to biweekly) of the debriefings of Knowledge Forum discussions. During these sessions, discussion threads were projected on the classroom screen, and students were given explicit instruction in ways to apply specific discourse scaffolds—especially *challenging ideas*, *extending ideas*, and *the big picture*—in an attempt to move discourse further along. These face-to-face learning activities presented models from the previous day’s discussion posts of effective student use of extending, justifying, or challenging peer’s posts with appropriate reasoning and constructive discourse. The teacher would lead discussion on how and why a discussion thread moved ideas deeper into the text and evidenced appropriate literary reasoning. Additionally, a student discussion thread that did not advance beyond a question or brief response was presented to the entire class, and a specific discussion scaffold, such as *challenging ideas*, was modelled by the teacher. Students practiced writing build-on posts applying this scaffold until they could apply these discourse moves independently. In short, instructional scaffolding of how, when, and why to use specific discourse moves was taught until student work evidenced mastery.

Discussion scaffolds and sentence frames equated with literary reasoning and argumentation. Language shapes thinking. Prior to the implementation of the intervention, Mrs. Fleck, the classroom teacher, lamented the lack of student discussion that went deeper into the texts. “My students,” she noted, “will answer questions about plot or character, or when asked to make a connection or prediction will share something, but there’s no building upon others’ thoughts or listening to each other.” Over the course of the intervention, students grew in their selection and application of extended discussion scaffolds, such as *challenging* and *justifying ideas*, and the online discussion threads presented here demonstrate students applying the literary reasoning and discussion skills to sustain in-depth literary talk using digital tools. I attribute these findings to Knowledge Forum’s potential to identify, explicitly model, and scaffold cognitive processes associated with progressive, literary discourse.

In Phase 2 we applied the common practice of providing sentence starters or frames for face-to-face or written discussions to digital discourse (see Appendix A). Students were required to employ these with every computer session and classroom discussion. As the data indicate, there were quantitative improvements in the students’ deep literary understanding during Phase 2, and chi-square analyses support the conclusion that instructional changes made between Phases 1 and 2 had a measurable effect. The sentence starters enabled students to internalize the language to shape the thinking that deepened discussions in a constructive and collaborative manner.

Future Modifications

Despite introducing the *big picture* scaffold and thinking during Phase 2 of the intervention, there was little evidence of students selecting and applying this scaffold during Knowledge Forum discussions. The intent of the big picture scaffold is to propel student discussions to look beyond the text and make connections to other texts, personal experience, or ways the text helps them understand themselves or the world around them. Additionally, the big picture scaffold was intended to help students look for connections between online discussion threads covering different topics and seek ways to bring about coherence of ideas. For example, Knowledge Forum debriefing sessions attempted to provide instructional scaffolding teaching students how to bring various discussion thread topics (e.g., plot, characterization, and symbolism) together, analyzing and synthesizing them into an overall interpretation of the text. The goal was

to help students develop literary interpretations over time, to observe how their interpretations were developing by looking back at previous discussion threads. There was no evidence of students looking backward and synthesizing ideas from previous discussion threads.

As clarifying understanding over time is a cognitive reasoning process associated with strong readers, future modifications to the intervention might examine ways to explicitly model and guide students to make connections across discussion threads. Literary analysis is equated with synthesizing elements, such as plot and characterization, with authorial moves, such as linguistic devices, symbolism, and tone, into a coherent, overall interpretation of text. Future modifications might examine ways to propel students to use digital tools to mimic this kind of literary reasoning and argumentation. It may be as simple as teaching students to use digital tools to identify keywords and link discussion threads by topic or ideas. This might better contribute to student awareness and application of discussions that bring about coherence of differing threads.

Discussion

Asynchronous, online discussion forums are potentially ideal for the social construction of knowledge, yet these often fall short of this objective. This study took up the challenge of adapting online learning environments, such as Knowledge Forum, to instruct students in the discussion and thinking appropriate for advancing knowledge in the literature classroom. The goal of this design-based experiment was to develop a theory of instruction, grounded in the real world of the classroom that addressed how using online discussion forums might enhance students' ability to learn progressive, knowledge-building discourse in ways appropriate to the ELA discipline. If effective, it would also satisfy the need to train students in 21st-century learning practice and skills.

Empirical studies within the literacy research field have established a connection between dialogically organized instruction and improved student textual comprehension. A knowledge-building approach to literature instruction—to borrow a concept from Nystrand (1997)—ups the ante for conceptualizing what dialogically organized instruction might teach through its emphasis on progressive discourse. Describing effective dialogic episodes correlated with high levels of students literary understanding, Nystrand et al. (1997) noted the importance of teacher uptake moves that “restate” and “orchestrate” moving discussion forward. They up the ante by probing and pushing students to expand, modify, justify, clarify, and confirm their thoughts and orchestrate and focus whole class response. The data presented here suggest that teaching students to notice and note textual elements on their own and socially construct textual interpretations engaging in progressive, online discourse scaffolded by Knowledge Forum, helps students learn to up the ante themselves by applying the disciplinary literary reasoning associated with how knowledge is constructed, argued, and advanced in the ELA classroom.

This capacity to up the ante is attributable to Knowledge Forum's potential to identify, explicitly model, and scaffold cognitive processes associated with progressive, literary discourse. In the effective dialogic classroom, teachers up the ante by asking students to rethink, justify, add information, and challenge the interpretations of others. In the case of this design-based experiment, I theorized that Knowledge Forum's theory-building discourse scaffolds could be replaced with scaffolds mimicking teacher discussion moves equated with deep comprehension of texts. Students demonstrated that they could apply the ways that English teachers typically uptake student responses during classroom discussion. In the present study, students mirrored the moves teachers normally make in guiding classroom discussions and made them on their own, enhancing the quality of constructive and collaborative progressive discourse. This was brought about by programming teacher uptake

moves into the Knowledge Forum scaffolds. Thus, because students were required to select a scaffold focusing their discussion contribution, they learned to internalize and apply effective, literary discourse norms. The literary scaffolds *I want to talk about*, *I have a question*, *challenging ideas*, *extending ideas*, *justifying ideas*, and *the big picture* played an essential role in the study's positive outcomes.

These literary discourse scaffolds also supported student mastery of the unique ways knowledge is constructed when discussing literature. In the literature classroom, we want students to form interpretations, extend them by identifying macrotextual patterns, engage in inferential thinking, and state analyses supported by evidence. The literary scaffolds made the nature of literature discussion explicit and reinforced student internalization of ways of thinking associated with strong readers. In an era in which educational researchers and practitioners seek to make teaching and learning more active and participatory, this study demonstrated that students could engage in deep discussion of text without teacher direction. More than applying constructivist approaches to learning, students were creating knowledge precisely because they learned the ways to talk about and build understanding of a text, rather than taking in teacher observations about a text's meaning.

A reasonable conclusion from the data presented here is that students demonstrated application of progressive, literary discourse and knowledge construction because the scaffolds programmed into Knowledge Forum facilitated student learning of these higher order reasoning skills. Proponents of dialogically organized instruction have suggested that practitioners adopt ways to frame students' thoughts via explicit instruction in the ways of initiating and entering into classroom discussions about text, typically supported by giving them sentence starters, the language with which to initiate what they want to say (Adler & Rougle, 2005; Langer, 2011). The daily practice in class, the constant requirement to select a scaffold appropriate for posting an original note or building on the ideas of others, helped students internalize the structure and shape of literary thought and discourse. Student discussions on Knowledge Forum did not fizzle out or result in excessive "good idea" or "interesting" comments that imply value but ultimately go nowhere, as is often the case in digitally mediated dialogue. These students were moving literary understanding deeper because the scaffolds they chose required them to do so.

Limitations and Implications

This design-based experiment produced a theory of instruction tracing the achievement of an educational objective and the modifications to learning activities and the classroom environment that brought students closer to the stated goal. Correlation or causation cannot be established; an experimental or quasi-experimental study should be the next step in measuring the efficacy of the instructional methods established in this study on developing progressive, online discourse. Because lasting effects of interventions on student learning require time, it makes sense that further research should be at least one year in duration rather than the one semester in this study. Future research investigating the efficacy of progressive, literary discourse on ELA curricula needs to encompass a variety of school contexts, grade levels, and content.

By turning over responsibility for understanding texts entirely to the students by using an online environment, and by teaching them how to engage in extended, collaborative knowledge building around literary interpretations, we have the potential to understand much more about how to improve the teaching of ELA curricula and the central role online discussion forums may play in enabling students to create deep understanding of content.

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Appendix A

Table A1

Sentence Starters for Literary Knowledge Building

Knowledge Forum scaffold	Sentence starters
I want to talk about	I want to talk about . . . I noticed . . . As I was reading I noticed . . . After reading/discussion I noticed . . .
I have a question	What still confuses me is . . . I don't understand . . . I wonder why . . . What if . . . Why is it that . . .
Challenging ideas	I have a different idea . . . I'm not sure I understand. Could you show me something in the text that makes you say that? I disagree with you because . . . Everyone seems to think _____ but I think . . . What in the text makes you believe that?
Justifying ideas	This makes sense to me because . . . I agree with you because . . . While I realize _____; I think _____ because . . .
Expanding ideas	This reminds me of . . . At first I thought _____; now I think . . . A part of the text that makes me believe this is . . .
The big picture	Maybe this book is about . . . I think it means _____ because . . . In the end I believe . . . My conclusion at this point is that . . .

#DigPed Narratives in Education: Critical Perspectives on Power and Pedagogy

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Abstract

This mixed methods study addresses a knowledge gap in the nature and effects of networked scholarship. We analyze #DigPed, a Twitter hashtag on critical pedagogy, through the lens of Tufekci's *capacities and signals* framework in order to understand how educational narratives develop and spread on #DigPed. Using social network analysis and thematic analysis of content, we identify three prominent narratives in the network and discuss the network structures from a critical perspective. Based on the findings, we propose *pedagogic capacity*—the power to initiate a productive and potentially transformative educational discourse, within oneself and within communities—as an additional lens to explore the spread and impact of critical narratives in education. Findings confirm the view that networked spaces are organized by hidden hierarchies marked by influence.

Keywords: #DigPed, critical online pedagogy, gatekeeping, hashtag community, networked participatory scholarship, pedagogic capacity, Twitter

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#DigPed Narratives in Education: Critical Perspectives on Power and Pedagogy

When boyd (2010) coined the term *networked publics*, which she defined as “publics that have been transformed by networked media, its properties, and its potential” (p. 42), the idea of collective digital spaces was relatively new among scholars. For many, participation in networked spaces was not part of everyday academic practice or even vocabulary. Yet, these spaces have increasingly become places for public scholarship. Twitter in particular, with its ease of use and capacity to build personal learning networks, has quickly become a place for *networked participatory scholarship* (Veletsianos & Kimmons, 2012), or simply put, academic participation. Stewart (2016) commented that “scholars who are isolated, disillusioned, marginalized, or junior in their institutional scholarship” could have a voice on Twitter, building identity and meaningful connections. However, as Stewart (2016) also noted, the form and “effects of networked scholarship” are understudied in education (p. 62). In this study, we address this ignored yet significant area of research by exploring a Twitter hashtag with a focus on digital pedagogy: #DigPed.

Background

Hashtags can be defined as “the practice of adding a keyword, or set of keywords, to a Twitter post” (Koutropoulos et al., 2014, p. 12). These keywords allow users to categorize messages, and as such they are “ad-hoc solutions” (p. 12) to organize and make sense of incoming and outgoing messages. The creation of hashtags is not just a technical solution to make sense of abundant information in an open platform; they are also communicative acts. Yang (2016) argues that hashtags are narrative forms because they tell stories (for example, the hashtag #BlackLivesMatter and the associated movement began after the tragic death of African-American teenager Trayvon Martin). By posting a tweet with a hashtag, we invite people to participate in the “co-production of stories” (Yang, 2016, p. 14); however, there are no temporal or communal boundaries to these stories. As long as the platform exists, any post can be quoted, retweeted, liked and commented on anytime, by anyone.

Recent studies suggest that educators increasingly use Twitter for building personal learning networks and for professional development opportunities that do not necessarily fit into traditional practices (Carpenter & Krutka, 2014; Veletsianos, 2012). In a mixed methods study, Forte, Humphreys, and Park (2012) observed that Twitter was a powerful tool to bridge new ideas circulating on networks with local communities. The authors noted the following:

We argue that this “bridging” activity not only helps teachers generate social capital that can help them succeed in their careers, but that it is the kind of social substrate that is necessary for education reform efforts to take root as like-minded individuals strengthen one another’s ability to effect change. (p. 106)

Hence, the authors posited that teachers’ activities on Twitter could be considered “grassroots professional development efforts” with transformative power (p. 106). Similarly, Fang (2016) asserted, “[e]veryone’s journey towards self-transformation is unique. For many, it is likely to begin with a hashtag” (p. 141).

Yet, access to digital networks does not necessarily prompt meaningful participation, as many scholars have noted before us. Resistance to open structures might occur, especially if they seem unfamiliar or if they are not part of everyday practices (Iiyoshi & Vijay Kumar, 2008). Active participation on a platform like Twitter also requires users to have certain digital literacy skills, such as finding the right balance between private and personal, being able to weed out fake or irrelevant information, and having an awareness of their imagined and real audience. This digital literacy skillset is particularly important for users to develop in hashtag communities because “network platforms are increasingly recognized as sites of rampant misogyny, racism, and harassment” (Stewart, 2016, p. 62). In addition, the stories told via hashtags, may not be very linear, or clear-cut, as in traditional narrative forms. Users can create *secondary hashtags* by creating, using, and disseminating additional keywords, thus creating and promoting the growth of subcommunities. However, the flow of information (the number of stories told) and participation patterns can be chaotic, as the perception of time is vague in these spaces, and hashtags have the potential to link past, present, and future communities.

Another important issue to bear in mind is the values inherent in technology. As Veletsianos and Kimmons (2012) noted, “practices developing in conjunction with emergent technologies (e.g., Facebook, Twitter, Google) will be influenced by the embedded values of those technologies and that not all of these influences may be positive” (p. 179). For example, Twitter algorithms may gently force or unconsciously lead us to swim in our own bubbles. Indeed, citing Gillespie (2014), Bruns and Burgess (2015) argue that we need to consider the shift from networked public and ad hoc publics “to personalised, calculated publics” because of the algorithms that are imposed on us (p. 25).

Considering the unique affordances of the Twitter platform—both negative and positive—we seek to understand the kinds of narratives that spread in the #DigPed network and their nature, as further explained in detail below.

Research Context

Digital Pedagogy Lab (DPL; <http://www.digitalpedagogylab.com/>) is a project that is committed to the “ongoing investigation and creative implementation of critical and digital pedagogies” (DPL, n.d.). As such, the project is “not ideologically neutral” and is influenced by the work of seminal critical pedagogues like Paulo Freire and bell hooks. Through face-to-face and online professional development opportunities and educational outreach, contributors to DPL aim to deepen the conversation around critical approaches to education and empower both learners and teachers.

DPL is present on Twitter (@DigPedLab) and uses the hashtag #DigPed to reach a broader audience and engage people with critical pedagogy. This research focuses on the #DigPed activities during three DPL events: Digital Pedagogy Lab Cairo (March 20–22, 2016), Digital Pedagogy Lab PEI (July 13–15, 2016), and Digital Pedagogy Lab 2017 Summer Institute (August 7–11, 2017). These were face-to-face professional development events with online components, such as virtual meetings, Twitter chats, and blogging.

Conceptual Framework

In this study, we explored #DigPed posts during three DPL events held between 2015 and 2017. The initial goal was to understand how educational narratives developed and spread on #DigPed and the nature of their capacities using Tufekci’s (2017) *capacities and signals* framework as an orienting lens. Here, by educational narrative, we refer to educational stories—in other words, a series of connected events, created via the use of hashtags.

Tufekci argues that the strength of social movements does not lie in their size or scale; rather, “strength of social movements lie in their capacities,” and these capacities are signaled through collective action and impact. Here *capacity* means the power to successfully spread a vision (“setting the narrative”) and change policy and practice (“effect electoral or institutional changes, and to disrupt the status quo”) (2017, p. 191). Tufekci describes three arenas of capacity in her analysis:

1. Narrative capacity: “The ability of the movement to frame its story on its own terms, to spread its worldview” (p. 192).
2. Disruptive capacity: The ability of the movement to “interrupt the regular operations of a system of authority” (p. 192).
3. Electoral or institutional capacity: The ability to force political and institutional changes through both “insider and outsider strategies” (p. 192–193). (In this research, we do not focus on electoral capacity due to the research scope.)

We used the capacities and signals framework because it allows us to ask intriguing questions about the power and impact of hashtag communities on educational practice. Using the capacities and signals framework, we conceptualize Twitter as a politically charged public space, where educators occasionally act against mainstream models and common practices in education through a complex interplay of individual performance, spontaneous interactions with others, and organized structured and semistructured events. We acknowledge the fact that #DigPed chats are not intended as protests in a traditional sense, and using a sociopolitical framework to analyze its activities as political movements may seem unfitting. However, as we noted above, DPL is a project which is not ideologically neutral: It is inspired by postcolonial movements in education. Perhaps because of this ideological positioning,

discursive protests against mainstream models and practices in education are often present on #DigPed, whether intentional or through spontaneous interactions.

Second, our goal was not to adopt the conceptual framework blindly. Rather, we used it as a starting point to ask such questions and embraced a critical perspective to be able to discuss to what extent the framework may apply to the unique context of #DigPed. We also intended to explore whether the framework was sufficient to explain educational narratives or whether we needed any other capacity type for such instances.

Research Question

The purpose of this research was to examine #DigPed conversations through the lens of the capacities and signals framework. The overarching research question that guided this research was this: How do educational narratives develop and spread on #DigPed?

Methods

Research Design

In this study, a transformative mixed methods design is used. Different from basic mixed methods designs, transformative mixed methods design encases the design within a conceptual framework (i.e., in the context of this study, the capacities and signals framework) and benefits from it as an overall orienting lens (Creswell & Plano Clark, 2011). This type of mixed design is value based and ideological (Greene, 2007), and the adopted framework shapes many aspects of the research, such as data collection, analysis, and interpretation (Creswell, 2012).

Data Sources

The main data corpus included both quantitative (numeric) and qualitative (textual and visual) data. The primary data source was all the Twitter posts tagged with #DigPed during the three DPL events. Secondary data sources were information on DPL event websites, keynotes, and blog posts linked to Twitter posts.

Sampling

By adopting a convenience sampling strategy, all Twitter posts tagged with #DigPed during three DPL events were sampled. These events were held between 2015 and 2017. We analyzed 385 interactions among 175 participants in #DigPed Cairo, 115 interactions among 75 participants in #DigPed PEI, and 530 interactions among 229 participants in the #DigPed 2017 Summer Institute.

Data Collection & Analysis

Social network analysis (SNA; Hansen, Shneiderman, & Smith, 2010) was used as a starting point in this research. To do this, all network activities in three DPL events were collected with an SNA software called NodeXL. Following that, local and global network metrics were calculated for each event, and sociograms were created based on these metrics to examine the network patterns. To visualize sociograms, grid layout (Hansen et al., 2010) was selected, and nodes were grouped into clusters using the Clauset-Newman-Moore cluster algorithm (Clauset, Newman, & Moore, 2004). In addition, we examined other metrics provided by the software, such as top URLs, top domains, top hashtags, and top words used for each event.

We then employed thematic analysis using the constant comparative method (Charmaz, 2006; Tracy, 2013) to (a) contextualize findings obtained from the SNA and (b) identify

prominent narratives that had spread on the network. This part of the study was approached through an interpretive paradigm; that is, we acknowledged the fact that knowledge is “socially constructed through language and interaction” and is always partial (Tracy, 2013, p. 41). Thus, we sought understanding through self-reflexivity and iterative cycles of data analysis. We kept a collaborative researcher journal to increase our self-reflexivity and as a space to document our thoughts.

Thematic analysis began with the data provided by NodeXL. The program provides useful information, such as all tweets posted and their weight in the network (the posts that gained the most attention in the network) and the most commonly used hashtags and words. We first made a note of data that piqued our interest. For example, in #DigPed Cairo, *love* was one of the most common words used in few clusters of activity. However, what did that mean in context? In order to better understand the context of quantified information and to identify other possible prominent themes in the network, we then examined the #DigPed posts for each DPL event using thematic analysis.

First, both researchers read all the event tweets and noted initial impressions. They then had a meeting to discuss these initial thoughts and ideas. After this initial exploratory stage, Researcher A began coding all tweets in a more systematic manner. Tweets were open coded using a codebook, and codes within and across events were refined in an iterative manner (for an example of open codes, see Appendix A). The next step was to identify common codes within and across each event through axial coding. At this stage, Researcher B was invited to review the emerging codes and note areas of concern. Finally, after the researchers reached consensus, the codes that were most relevant to the goals of the research study were chosen through selective coding. While doing that, additional data sources linked to the posts—such as event websites, streamed keynote sessions, and blog posts—were also examined to further contextualize the data. For example, after analyzing all the tweets for #DigPed 2017 Summer Institute, we understood why www.theedadvocate.org appeared as one of the most visited domains in the SNA (further discussed in the Findings section). Multiple readings of both SNA and event tweets were required to make such connections. Researchers regularly held online meetings and had chats to discuss such emergent findings.

During the research process, reflections and questions arising from the analysis were noted in the coding documents where appropriate and in the researchers’ shared reflective journal (for an example, see Appendix B).

Results

Social Network Analysis

Network patterns. We first created a visual representation of the social relationships within the network using a sociogram (Figures 1, 2, and 3). In sociograms, each node represents an individual in the network and each tie represents an interaction/conversation among them. Local and global network metrics were calculated, and sociograms for each event were created based on these metrics. To visualize sociograms, grid layout was selected, and nodes were grouped by cluster using the Clauset-Newman-Moore cluster algorithm (Clauset, Newman, & Moore, 2004). The tie colors, widths, and opacities are based on edge weight values. The edge widths are based on edge weight values. The nodes’ sizes and opacities are based on betweenness centrality values. The colors of the nodes were randomly assigned according to the clusters they belong to.

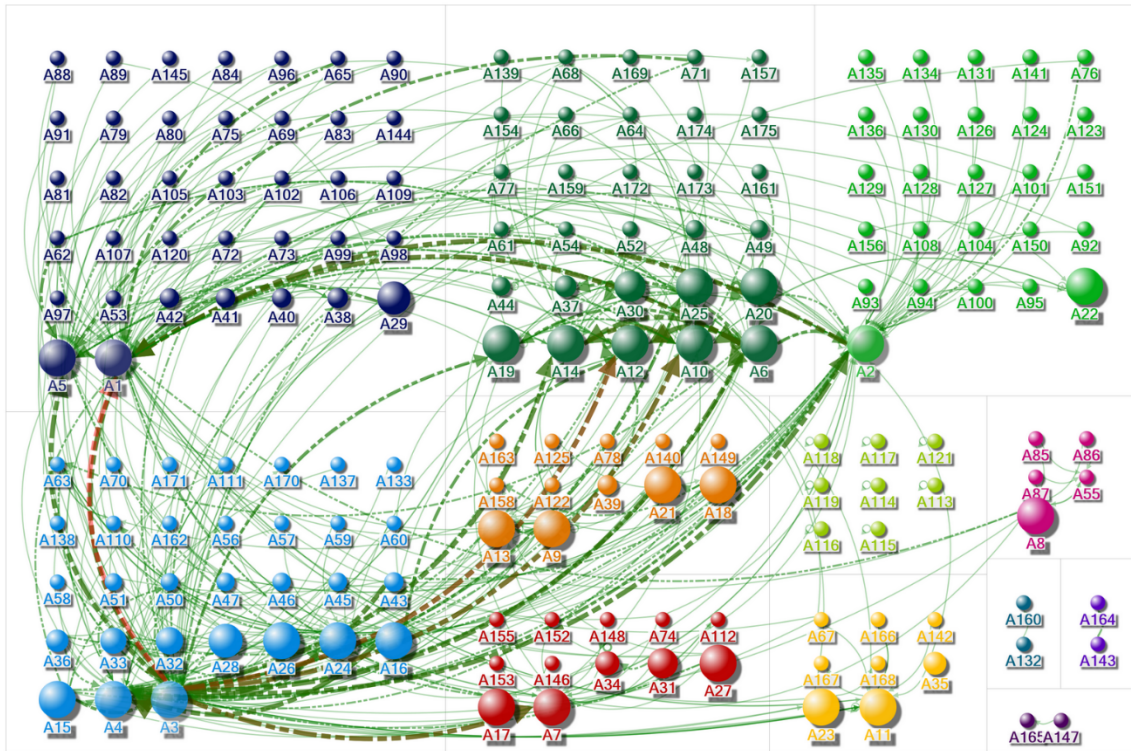


Figure 1. Sociogram for #DigPed Cairo.

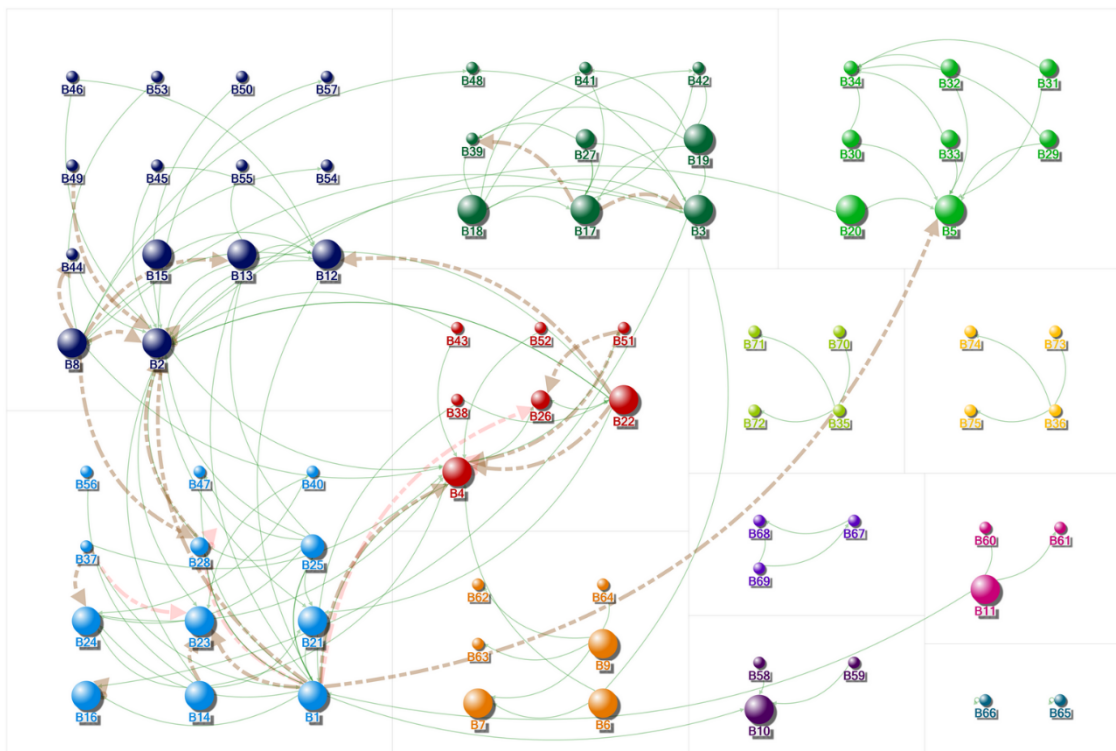


Figure 2. Sociogram for #DigPed PEI.

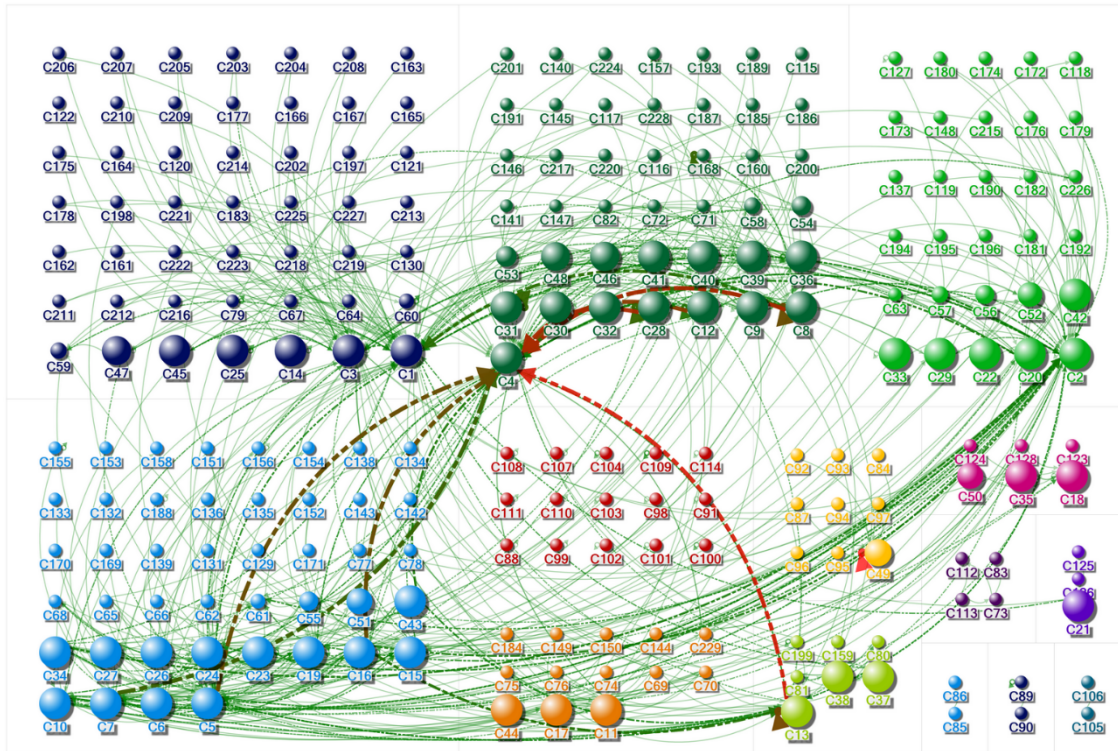


Figure 3. Sociogram for #DigPed 2017 Summer Institute.

Based on Smith, Rainie, Shneiderman, and Himelboim’s (2014) classification of Twitter conversations into six types, we identified #DigPed Cairo, #DigPed PEI, and #DigPed 2017 Summer Institute as unified-tight crowd networks, in which discussions are characterized by highly interconnected people with multiple connections and few isolated participants. In such networks, ideas and conversations can circulate very fast in the conduits of the network because of the tightly woven network connections.

The sociograms above further show that the #DigPed network was not controlled by a single person, which is something that is typically observed in what are known as *ego networks*. That is, rather than depending on a focal node/person, power was distributed among different groups of people with a few key influencers more or less in each cluster. These sociograms also show how the conduits of the network formed and how conversations spread across these conduits. Besides, each participant can be located, and their position can be examined through the sociograms.

Hashtags used. To better understand the capacity of the #DigPed network, we examined the hashtags posted during the events. Hashtags serve as gates that link different networks—and communities—to one another in the networked universe. Thus, they are crucial for seeing how dissemination occurs and what other communities are linked to #DigPed’s discourses. We examined conversations for each #DigPed event using NodeXL to identify the most used hashtags. The top 10 hashtags for each network were listed, and a cross comparative analysis was conducted (Table 1).

Table 1

Top Hashtags Used During Three DPL Events

DigPed Cairo		DigPed PEI		DigPed 2017 Summer Institute	
Top Hashtags	Count	Top Hashtags	Count	Top Hashtags	Count
digped	342	digped	95	digped	684
connectedlearning	6	highered	11	dplintro	38
unfis15	5	opendata	10	edchat	32
dgst101	5	oer	6	edtech	11
epl521	5	oa	6	dpintro	6
highered	5	openaccess	6	tweetyourshoes	6
editorspicks	5	twitteressay	3	sixwordintro	6
edtech	4	edtech	3	highered	6
sketchnotes	3	clmoooc	1	datalit	6
indieweb	3	bonfire	1	InstructionalDesign	3

#DigPed was naturally the leading hashtag in all events. In addition, in all #DigPed events, #highered was a common hashtag, which suggested that higher education was the target audience.

Overall, the use of secondary hashtags during DigPed Cairo, DigPed PEI, and DigPed 2017 Summer Institute was weak compared to the use of the main hashtag (#DigPed), which suggests that links to outer networks were also weak. However, it should be noted that some other means, such as blogs, live chat sessions, and so on, were also used during event, and this finding is open to further interpretation.

Key influencers. This part of the analysis focused on key nodes—in other words, hubs in the #DigPed network during each DPL event. The purpose of this analysis was to identify key influencers and see how power was distributed among other nodes. In order to identify key influencers, we examined participants' betweenness centrality values (Table 2). *Betweenness centrality* is an SNA metric that indicates a node's ability to bridge different nodes and subnetworks. The higher the betweenness centrality value, the stronger and more critical positions can be held in the network.

We first ranked the participants from highest to lowest according to their betweenness centrality values. Following that, we noted the top 20 participants in each event to identify those leading and shaping the #DigPed network and to find out whether specific nodes dominated the #DigPed network during and across each event.

Table 2

Top 20 Participants According to Their Betweenness Centrality Values

DigPed Cairo		DigPed PEI		DigPed 2017 Summer Institute	
Node	Betweenness Centrality	Node	Betweenness Centrality	Node	Betweenness Centrality
A1	7414,494	B1	1554,94	C1	12183,33
A2	6600,591	B2	1153,96	C2	7664,48
A3	5691,543	B3	905,30	C3	6501,44
A4	3934,067	B4	795,41	C4	6162,40
A5	2934,341	B5	680,80	C5	3430,62
A6	1936,178	B6	583,62	C6	2414,87
A7	1882,262	B7	456,00	C7	2253,84
A8	1251,000	B8	432,51	C8	2224,78
A9	1194,656	B9	354,00	C9	1891,21
A10	1152,243	B10	238,00	C10	1763,33
A11	1038,979	B11	238,00	C11	1735,54
A12	1008,478	B12	233,59	C12	1640,93
A13	864,151	B13	154,12	C13	1409,80
A14	720,589	B14	152,90	C14	1152,00
A15	506,833	B15	121,74	C15	1132,14
A16	469,451	B16	118,82	C16	1118,34
A17	405,111	B17	108,57	C17	1074,50
A18	372,083	B18	102,83	C18	983,65
A19	367,353	B19	102,83	C19	815,42
A20	347,682	B20	95,86	C20	792,59

According to the analysis based on betweenness centrality metrics, we observed that, in addition to participants (via face-to-face and online means), facilitators and speakers in DPL events held strategic locations in each #DigPed event. However, the similarity of their betweenness centrality metrics indicate that power was not gathered on a specific node, in contrast, the power of the network was distributed among the top influencers.

Thematic Analysis: Common Themes Across Events

In this section, similar patterns across all events are noted. All names are anonymized by assigning codes for each participant and for each event.

Strong community. In all events, the sense of community in the network was strong, especially among some of the key influencers we identified via SNA (e.g., A34: “This makes me feel grateful for the *community* that is #digped et.al. What We Need Is Here”; B1: “So grateful for the time I had @dipedlab PEI and the friends I met. Thanks to B5 B4 B26 B23 #digped”; A2: “Me and my dear friends A1 and A7 at ‘the end of all things’ (for now) @dipedlab Cairo. #digped”).

The community included both on-site participants and online participants who were following the events via Twitter (e.g., A6: “I’m so glad the #DigPed discussion is ongoing. I’m definitely keeping the @TweetDeck column in place for good :)”; C33: “Missing being at Digital Pedagogy Lab this year...but following along from home #digped”).

Participants also introduced people to one another online (e.g., B8: “B53 I want you to meet my friend, B44 #digped [Name X], meet [Name Y]. [Name Y], meet [Name X]. Now- go change the world of digped”); crowdsourced resources (e.g., B2: “Who should I connect to this #digped work group on using #opendata/analytics in #highered? #oer #oa #openaccess”); and

shared their lived experience with others (e.g., A26: “All checked in ... almost finished packing ... of to @DigPedLab tomorrow #digped ... looking forward to seeing C5 and many others ..”).

Virtually Connecting. In each event, Virtually Connecting, defined by the creators as “a connected learning volunteer movement that enlivens virtual conference experiences by partnering those that are at the conference with virtual participants that cannot attend” (Bali, Caines, deWaard, & Houge, 2016, p. 212) was a venue to bridge on-site and off-site experiences (e.g., C40: “Check out this @VConnecting session with me and a group of other rowdy and generous #digped troublemakers”; C55: “You can call me a #digped follower, advocate, and fan! Today, I’m a lurker in the @VConnecting session that C10 is leading :) THANKS!”). This finding is also strengthened by the SNA, as Virtually Connecting was one of the top-visited URLs in all three events.

Limited evidence showing impact. The posts showing impact were limited, although some posts clearly showed a positive change in participants’ (online and on-site) lives, including the facilitators of the event (e.g., B1: “Small shifts this week, huge shifts in my life last 5 years thanks to you all. #digped”; C5: “Today feels like the beginning of a lifechanging experience for me: co-teaching networked/intercultural learning at #DigPed w C15”).

Thematic Analysis: Prominent Narratives Within Each Event

In this section, we present the most prominent narratives within each event using thematic analysis. We observed that although participants often shared educational technology tips and advice during the events, the narratives that gained most attention were related to broader pedagogical visions and ideals that evoked strong reactions in #DigPed participants. Each of the narratives below originated from either a DPL facilitator or a keynote speaker.

Narrative 1 (#DigPed Cairo): “Love in pedagogical work is an orientation.” Love in education was the most prominent narrative in #DigPed Cairo. The narrative emerged from a discussion in a keynote session, which prompted another DPL facilitator to write a reflective blog post and share it at #DigPed. This post, titled “On Love, Critical Pedagogy, and the Work We Must Do” (Morris, 2015), was the top URL in the network. Participants either retweeted this post directly (without additional comments) or quoted sections of the post they wanted to share with others. Here we observed how scholars who share similar pedagogical visions amplify and further develop one another’s ideas using online and face-to-face opportunities.

Session discussions on love elicited strong emotional reactions from the network, especially from one of the facilitators (e.g., A3: “why is it painful for the academic to admit that love stirs them?”; A3: “One of my fave quotes like...ever A25, A7 #DigPed. Also: internet has a heart? Internet has a heart!”). Although some participants questioned this narrative, counterperspectives were limited. On one occasion, we observed that a counterperspective was shut down immediately (i.e., A18: “A4, A158, A21 but scale’s a big barrier, and I think love is the wrong word. #DigPed #hippydippy”; A9: “A18, A4, A158, A21: no I think love is the right word #digped”).

Discussions on love also spread to a Virtually Connecting session (i.e., A3: “Are we being colonial with our love?” asks the insightful A11 on @VConnecting from #DigPed”).

Narrative 2 (#DigPed PEI): “Every student can have their own domain – to share their work, knowledge, memory.” In #DigPed PEI, multiple interrelated narratives on open education were present on the network. The keynote *Memory Machines: Learning, Knowing, and Technological Change* by Audrey Watters (2016) seemed to gain attention most and prompted discussions on student agency, students’ ownership of their data, open data, and access. When the keynote speaker mentioned Domain of One’s Own, a University of Mary Washington project, tweets about how it might contribute to student agency quickly spread on

the network (e.g., B24: “@audreywatters: Domain of One’s Own is one of the most important commitments to memory an institution can make #digped”; B1: “‘Every student can have their own domain -- to share their work, knowledge, memory.’ B23 on Domain of One’s Own #D...”; B2: “No-cost is not the same as free. Our students pay Google with their data. And we’ve done this without their consent. B23”).

The number of tweets posted on this narrative is limited in the data set when compared to the narratives in other two events; however, a similar pattern emerged: An influencer (e.g., a keynote speaker, a facilitator) initiated an idea, which was then amplified through retweets and quotes by other users, including other key influencers.

Narrative 3 (#DigPed 2017 Summer Institute): “Most stories about student debts/struggles go untold.” This narrative emerged from a keynote session by Sara Goldrick-Rab (UMW Division of Teaching and Learning Technologies, 2017) on “a real but often-unrecognized crisis [in public education]: basic needs insecurity.” As the keynote speaker mentioned in her talk, “most stories about student debts/struggles”—such as student homelessness, debts, hunger—went untold, and the keynote was a platform to bring those issues to surface and call for action. As one participant (C7) tweeted, these were “sobering and sad stories” and gained much attention on the network. Another participant (C8) noted, “I’m moved by @saragoldrickrab focus that we create lots of false narratives about students and college #digped.”

Perhaps this narrative was the most activist of the narratives we’ve discussed so far, as the keynote speaker was not only calling for empathy for struggling students but also calling for action that will lead to positive change. Participants were encouraged to take action by introducing simple interventions into their teaching, such as adding a section about student well-being into their syllabus and by actively challenging ongoing practices (e.g., C40: “‘You have until tomorrow and then I’m going to call the newspaper.’ @saragoldrickrab on how to INSPIRE YOUR COLLEGE TO TAKE ACTION. #digped”). As one participant commented, this keynote was an “academic manifesto” (C111: “#digped #AcademicManifesto Keynote by Sara Goldrick Rab”). It is interesting to note that the keynote speaker used Twitter effectively to gain attention and invite people to the talk and the discussions—she was one of the top tweeters during the event and joined a Virtually Connecting session where she further discussed the issues in her talk with others (e.g., C29: “@saragoldrickrab: ‘framing of interdependence among learners w/in syllabus influences retention’ @VConnecting #digped”; C63: “Amazing conversation happening right now at @VConnecting on syllabi, student empowerment and care #DigPed”). Perhaps because of this focus on action, theedadvocate.org, a site “devoted to advocating for education equity, reform, and innovation,” was one of the most visited domains during the entire #DigPed 2017 Summer Institute.

Discussion

In this study, we explored #DigPed posts during three DPL events held between 2015 and 2017. Our goal was to understand how educational narratives developed and spread on #DigPed and the nature of their capacities using Tufekci’s (2017) capacities and signals framework as an orienting lens. Three prominent narratives emerged from SNA and thematic analysis: “love in pedagogical work is an orientation,” “every student can have their own domain—to share their work, knowledge, memory,” and “most stories about student debts/struggles go untold.”

The narratives that widely spread on the network were not politicized enough to fit directly into the capacities and signals framework. The nature of these narratives led us to

consider a capacity different from the ones proposed by Tufekci (2017): pedagogic capacity. Here, we define *pedagogic capacity* as *the power to initiate a productive and potentially transformative educational discourse, within oneself and within communities*. In addition, we observed that narrative capacity could not simply be explained by spreading a vision: Educational discourses on an open platform like Twitter may evolve and grow in many unexpected directions with active participation, and as such, they open a space for dialogue, not manipulation or imposed action, as we would find in political discourses. Thus, in the context of education, more specifically from a critical viewpoint, we argue that there is a need to consider the pedagogic capacity of critical discourses in tandem with their narrative capacity. This relationship perhaps can be visualized on an x- and y-axis: While the y-axis shows how far a narrative spreads, the x-axis shows its depth from a pedagogical perspective. Research findings are discussed from this fresh perspective by taking the interplay of pedagogic and narrative capacities into consideration.

First, there was a strong sense of community on the #DigPed network, particularly among the facilitators. SNA findings also pointed to the formation of a tight community, which was characterized by highly interconnected people with multiple connections. Both facilitators and DPL participants (online and face-to-face), often shared their lived experience (local scenes, moments of anticipation, excitement, realization, etc.) as well as their professional activities publicly. This interplay of professional with the personal is also documented in the literature (see Quan-Haase, Martin, & McCay-Peet, 2015; Veletsianos & Kimmons, 2013; Veletsianos & Stewart, 2016) and is important for community building. However, because of the perceived connectedness and shared pedagogical values/cultural viewpoints, the pedagogic capacity of #DigPed may be limited. Indeed, although some participants demonstrated counterperspectives and were critical toward the ideas that were spreading in the network, this occurred rarely.

Second, educational visions (e.g., we need to embrace love in education) and facts that evoke strong emotions (e.g., student homelessness) seemed to gain more attention than simply sharing technology tools and tips, and thus, they had more pedagogic capacity. There seems to be a relationship between pedagogic capacity and community: The more comfortable people feel in a public networked space, the more likely they are to reveal emotions in response to a narrative and, hence, increase its pedagogic capacity. However, this argument is open to discussion, as there is a need to consider the complex nuances of community in networked spaces and what it means to share emotions with others in open online spaces.

Third, key influencers (i.e., organizers, keynote speakers) held strategic positions in the network. This observation was supported by the high betweenness centrality values identified via SNA. Thematic analysis also revealed that somebody influential in the network, such as a keynote speaker or an event facilitator, initiated all the narratives identified in this study. Ideas often went back and forth between these influential people and were amplified by others in the network. In addition, key people spread and amplified (a) their own voices through retweets and self-quotes and (b) the voices of people with similar pedagogical views. However, power (the strength of one's position in the network) was not held by a single person in the network, like we would observe in ego networks. Power was shared among a group of people, many of whom were key influencers. We argue that these people can be considered *de facto leaders*, as they are not expected to take formal leadership roles in online networks; rather, as Tufekci (2017) suggested, over time they “consistently emerge as informal but persistent spokespersons—with large followings on social media” (p. xxiii).

Here, we would like to elaborate on the concept of power and discuss how it relates to networked structures and to #DigPed in particular. Findings revealed that key influencers had

a strong capacity to gain attention. These people not only had large personal learning networks but also produced artifacts that stirred the community (e.g., a blog post or a keynote session). They seemed to be comfortable with being public online and were good speakers: They had charisma. In a way, key influencers had become *gatekeepers*: They acted as “innovator, change agent, communication channel, link ... opinion leader ... and facilitator” (Metoyer-Duran, 1993; we did not observe four of the roles suggested by Metoyer-Duran: intermediary, helper, adapter, and broker). Gatekeeping was distributed across face-to-face and online channels. It is important to note that in this context, gatekeeping was not manipulative or restrictive. Rather, it acted as a call to understand and consider a worldview; it was a pedagogical act. Thus, this research supports the perspective that gatekeeping is a “ubiquitous and diverse phenomenon” (Barzilai-Nahon, 2009; Gursakal & Bozkurt, 2017, p. 77). We observed that the #DigPed community reinforced the role of the gatekeepers by their responses to the emerging narratives.

Overall, findings suggest that although a network like #DigPed is open to all, *there are hidden power structures that shape the network activity*. Findings also align with Stewart’s (2015) argument that “hierarchies of influence relate to identity and attention, rather than [institutional] role” (p. 306) on an open platform like Twitter. These hierarchies of influence are not taught through formal practices (such as staff induction events or earned ranks) but learned and earned through ongoing participation in a community, both through professional and personal means. As Veletsianos (2012), citing Tufekci, noted “non-scholarly social interaction is ‘essential to forging bonds, affirming relationships, displaying bonds, and asserting and learning about hierarchies and alliances’ (cf. Tufekci, 2008, p. 546)”; however, these interactions may not necessarily “lead to positive outcomes” (p. 11).

Conclusion

Multiple implications in relation to pedagogic and narrative capacities of online networks like #DigPed can be drawn from this research.

There is a need to strengthen the pedagogic capacity of educational narratives: Blogs, Twitter chats, online meetings, and keynotes/talks can be considered intersectional spaces for critical discourse, as these spaces have the potential to cut across social identities (academic and personal), geographies (on-site and global), and time (past and present). Thus, these are powerful spaces for pedagogic practice: They have the power to initiate a narrative and open up venues for discussion, dialogue, and inspiration. However, in the context of hashtag communities, more effort is needed to reach a broader audience—an audience that goes beyond the immediate network community—and enhance the pedagogic capacity of critical narratives. A good example for strengthening narrative and pedagogic capacities is Audrey Watters (the keynote speaker at Digital Pedagogy Lab PEI). Watters, using her own resources, published the transcript of her DPL keynote talk on her site, which enabled others to access, amplify, and build on her arguments regardless of the extent of their engagement with #DigPed or DPL events. Another example for enhancing pedagogic and narrative capacities is Virtually Connecting (see Bali, Caines, deWaard, & Houge, 2016)—informal online meetings bridging onsite and offsite experiences—as it opens up a space of dialogue that is independent, inclusive, and organically developed. Effective use of hashtags might also increase the pedagogic capacity of a narrative, as hashtags are important outlets for connecting different communities with one another. All the narratives we have discussed in this paper have relevance to K-12 or adult education; however, in hashtag analysis we observed that #HigherEd was a common hashtag in all three events, and other areas somehow seem to have been ignored. With strategic use of hashtags, #DigPed’s critical discourses could be expanded more effectively to other formal and informal educational contexts.

There is a need to acknowledge the power dynamics in open networks: This research supports the perspective that online spaces are organized by hidden hierarchies marked by influence. The algorithms that are imposed on us and our everyday activities create a hybrid structure that shifts between horizontal and top-down structures. On an open platform like Twitter, although many voices can be heard and theoretically the space is open to all, people with influence still hold strategic positions in the network. In the #DigPed network, power was held by groups and was defined by relationships, similar pedagogic values, output, and presence.

Acknowledging power in open networks is useful for challenging false assumptions about openness—mainly the notion that open educational networks (like an educational hashtag community on Twitter) promote equality and lead to positive change regardless of one’s position in the network. Thus, we strongly echo Farrow’s (2017) call to develop deeper “critical reflexivity” (p. 142) in open contexts and argue for a need to have more discussions on privileged or subjective positions in networked communities.

There is a need to further investigate the complex nuances of gatekeeping: We call for a need to further investigate the nuances of gatekeeping and the types of capital that strengthen the positions of influencers, such as economic and social capital. It is important to note that social capital in online networks is strongly related to one’s capacity to influence. For instance, on Twitter, the number of tweets and their impressions, the size of one’s personal learning network, and the number of followers are mechanisms to determine capacity. However, mixed methods studies on capital in social networks should be conducted to better understand what these metrics might actually represent in social contexts.

Finally, we call for future research studies to explore the impact of critical educational narratives on practice and policy using qualitative methodologies. This is important, because metrics alone do not show us how narratives that diverge from common practices and norms may change people’s everyday practice and, equally important, how they are further shaped by lived experience. We aim to conduct a follow-up study on #DigPed narratives to tackle this complex, yet significant area of research.

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Author’s Notes

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The names bell hooks and danah boyd are intentionally written in lowercase because the cited researchers use their full names in this style.

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Appendix A

<i>Sample Open Coding</i>		
Tweet	Open Codes	Researcher Notes
A3: ““Love in pedagogical work is an orientation. It’s a commitment to the personhood of learners.’ #DigPed A1 [LINK]”	Q-Blog-Fac-Love (Quote, Blog post, Facilitator, Love)	A facilitator tweets a link to a blog post on love in education, written by another DPL facilitator (post is titled “On Love, Critical Pedagogy, and the Work We Must Do”).
B8: “B53 I want you to meet my friend, B44 #digped [Name X], meet [Name Y]. [Name Y], meet [Name X]. Now- go change the world of digped”	Fri-Bro-DigPedCo (Friendship, Brokering, Reference to DigPed Community)	Participant introduces a friend to another person online. There is a direct reference to DigPed: “the world of digped.” Could this be the online DigPed community? Added the code “Brokering” based on Metoyer-Duran (1993); search for more evidence on this.
C7: “Amazing narratives via @sarahgoldrickrab - many sobering and sad stories she shares some of her subjects. #DigPed”	Na-Key-EmRes (Narrative, Keynote Speaker, Emotional Response)	Participant reveals an emotion (sadness) in response to a narrative by Sarah Goldrick-Rab (keynote speaker).

Note. All names are anonymized by assigning a code for each participant and for each event.

Appendix B

<i>Sample Entries From the Researchers' Collaborative Journal</i>	
Date and Researcher Initials	Entry
Sept. 4, 2017 Aras Bozkurt & Suzan Koseoglu	<p>Suzan: Thinking about the narratives that have spread on digped, their reach... when were they most popular? Leaders in these narratives... (I think we can frame them as de facto leaders like Tufekci mentions in her book: not selected formally but they act as leaders.)</p> <p>Aras: (1) We can, maybe, talk about the “virality” of these thoughts... (2) Though very shallow, we can do sentiment analysis for each event, (3) as well as hashtags, we have also data for the most referred links. these can be examined as a source of data and discourses in these links, (4) to examine de facto leaders, we can examine these nodes (ppl) from different aspects: top-mentioned, top-tweeted, top-replied etc.</p>
Sept. 8, 2017 Suzan Koseoglu	<p><i>Reflecting on the Google Hangout with Aras.</i></p> <p>- Aras mentioned in the hangout that we don't swim in the same water on Twitter. How do algorithms impact our engagement with the hashtag? To what extent do we know about the algorithms imposed on us?</p> <p>We assume that Twitter is a networked public space; is it a space of “personalised, calculated publics” instead?</p> <p>- Researcher's involvement with the research field and how that impacts the process. How will the community feel about our findings? Our own assumptions and biases?</p>

Note. Researchers' collaborative journal was a space for the researchers to reflect on the research process and document their thoughts.

Increasing Interpersonal Interactions in an Online Course: Does Increased Instructor Email Activity and Voluntary Meeting Time in a Physical Classroom Facilitate Student Learning?

Bianca Cung and Di Xu
University of California, Irvine

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Abstract

Distance learning is expanding rapidly in universities. While theoretical and qualitative literature stress the critical role of effective interpersonal interactions in motivating students and facilitating learning in online environments, quantitative evidence on the benefits of increased interpersonal interactions on student learning outcomes is limited. This study examines the effect of providing a voluntary in-person meeting time in a physical classroom and increasing instructor email activity in a fully online precalculus course at a public university. We examine student final exam score and course grade as outcome variables. Student selection into courses was minimal since students only had access to one treatment condition at a time. We further used a propensity score matching strategy to address demographic variations in student characteristics across cohorts. Our results indicate that the increased interpersonal interaction opportunities increased final exam scores by 0.22 standard deviations and improved passing rates by 19 percentage points. Rosenbaum's sensitivity analysis indicates that it is unlikely that these results are due to omitted variable bias.

Keywords: at-risk students, computers and learning, educational policy, higher education, instructional technologies, instructional practices

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Increasing Interpersonal Interactions in an Online Course: Does Increased Instructor Email Activity and Voluntary Meeting Time in a Physical Classroom Facilitate Student Learning?

Online courses have taken a prominent role at many higher education institutions. Almost all public higher education institutions and two thirds of private institutions in the United States offer online courses (Allen & Seaman, 2014). Many institutions have been replacing traditional courses taught in physical classrooms with online courses as part of a long-term strategy to address

various institutional concerns, such as faculty and classroom space constraints, increasing enrollment size, and a greater number of adult learners with other responsibilities. This is especially the case for lower division courses with large student enrollments.

One attractive feature of online courses is the ability to use adaptive learning technology to personalize instruction in large enrollment courses, particularly those with students who start off with a varying range of background knowledge on the subject matter. By using algorithms to constantly update and tailor lessons to users, students can work with the computer specifically on topics that they individually do not know. Studies that previously examined online adaptive remedial math courses have found better performance among the online groups in both term-long courses (Fain, 2013) and accelerated summer courses (McGee, Vasquez, & Cajigas, 2014) compared to traditional term-long courses taught in a physical classroom. However, despite improvements in remediation, a large proportion of students still struggle in online adaptive courses. Students who struggle tend to have lower levels of self-regulation and motivation (Cho & Heron, 2015).

As with many other fully online courses, researchers are concerned about challenges that may hinder student learning, including the lack of human interaction in virtual learning environments (e.g., Anderson, 2003; Jaggars & Xu, 2016; Moore, 2013; Moore & Kearsley, 1996; Scardamalia & Bereiter, 2006; Su, Bonk, Magjuka, Liu, & Lee, 2005). Specifically, learning in a virtual learning environment not only imposes physical separation between students and instructors; the physical separation also creates a psychological and communication gap, what Moore (1991) defines as “transactional distance,” that leaves room for misunderstanding between instructor and learners. Additionally, the lack of interpersonal connections mitigates students’ sense of social presence in the course (Gunawardena & Zittle, 1997; Short, Williams, & Christie, 1976; Young, 2006) and works against the formation of a learning community.

In view of the challenges of learning in a fully online course, an extensive theoretical and qualitative literature stresses the critical role of building up effective interpersonal interactions in motivating students and facilitating learning in an online learning environment (e.g., Moore & Kearsley, 1996; Anderson, 2003; Scardamalia & Bereiter, 2006). Indeed, nearly every published online quality framework has emphasized the importance of interpersonal communication and collaboration (see Jaggars & Xu, 2016, for a comprehensive review of online design features).

Despite the consensus achieved regarding the importance of interpersonal communication, research has not yet identified specific ways to improve it in the particular context of college online courses. Instead, colleges and online course instructors are faced with a wide and confusing array of “best practices” that have been recommended under different frameworks for online course design with limited documentation and quantitative evidence on the benefits of these specific strategies.

This study sheds light on this issue by assessing some specific strategies to increase interpersonal interactions in a fully online entry-level college course using the adaptive tutorial system Assessment and Learning in Knowledge Spaces (ALEKS) as the main instructional tool. Specifically, we examine the academic outcomes of students in a fully online precalculus course at a large public four-year university given two conditions. The first condition, which we will refer to as the treatment condition, or the Online with High Interactivity condition (OHI), has frequent and regular email communications initiated by the instructors, in addition to an hour set aside each week for students to optionally meet in a physical classroom. We will refer to activities in which

participants need to be physically present, including the classroom meeting time, as *in person*.

Emails, which included announcements and reminders to keep students on track, were the primary mode of whole-class communication. The emails contained information that would typically be found in the announcements section of a learning management system (e.g., Jaggars & Xu, 2016). One advantage to the whole-class emails over posts in a designated course announcements section was that students could see the reminders before needing to log in to the course learning system, therefore reaching out to students in a more proactive manner. The control condition, or the Online with Low Interactivity condition (OLI), follows the typical design of fully online courses with a limited number of instructor emails and no organized in-person interactions. We took advantage of the fact that during the period of this study, only one treatment condition was offered during a particular term, and students were not aware which condition was offered when they enrolled in the course, thereby minimizing potential self-selection. We further used a propensity score matching strategy to address potential variations in baseline characteristics of the students enrolled in the course over time. The course structure was predetermined by the department, and in both years included in our study, the course used the same syllabus, online learning materials, and the same set of test banks for the final exam. We used several different course performance measures, including course grades, course passing rate, and a subset of questions from the final exam based on the same test bank, to uncover whether more regular instructor emails and voluntary face-to-face meeting time for answering student questions could improve student learning outcomes in this high-demand lower division developmental math course.

It is worth noting that our focus on the precalculus course is of particular importance for educational policy. First, remedial education has increasingly become an important feature of the U.S. higher education. Nationally, one third of college freshmen and sophomores take at least one remedial course in college (Skomsvold, 2014). Moreover, the remedial courses are also associated with particularly high failure rates. Based on student transcript data from a nationwide sample, a recent report by the U.S. Department of Education indicates that the number of postsecondary students who have ever enrolled in remedial coursework is closer to one half, with only 70% of the enrolled remedial coursework resulting in a passing grade (Radford & Horn, 2012). Among the large proportion of undergraduates that place into at least one remedial course, mathematics has the highest rate of remediation (Attewell, Lavin, Domina, & Levey, 2006; Chen & Simone, 2016; Parsad, Lewis, & Greene, 2003; Skomsvold, 2014; Sparks & Malkus, 2013) but the lowest rate of successful remediation (Bahr, 2011; Bonham & Boylan, 2011). Finally, due to the high demand and large volume of enrollment, lower level courses, such as developmental coursework, are most likely to be substituted by online learning. This is worrisome considering that recent studies have consistently found that academically underprepared students may struggle particularly in online learning (Asarta & Schmidt, 2017; Figlio, Rush, & Yin, 2013; Xu & Jaggars, 2014). Therefore, documenting and empirically evaluating the impacts of specific strategies and practices on student learning outcomes in precalculus online courses is of first-order priority.

Overall, this study seeks to answer the following research question: Do increased interpersonal interactions, as afforded by frequent instructor emails and the opportunity to meet in a physical classroom environment on a voluntary basis, improve student course performance? Our findings indicate that interpersonal interactions significantly improve student course performance in terms of all outcome measures, where the most convincing evidence is from the subset of final exam questions based on the same test bank. Our subsequent Rosenbaum's sensitivity analysis

(Rosenbaum, 2005) indicates that it is highly unlikely that these results are due to omitted variable bias. The evidence therefore suggests that students' achievement in an online course can be greatly enhanced with well-structured interpersonal communication through email and a weekly one-hour in-person meeting time for answering student questions.

Review of Related Literature

Interpersonal interaction is thought to play an important role in student learning (Moore & Kearsley, 1996; Anderson, 2003; Scardamalia & Bereiter, 2006). Collaborative work, for example, provides cognitive support and encourages critical thinking, problem solving, and deeper learning through the formation of a learning community (Fulford & Zhang, 1993; Kearsley, 1995; Moore & Kearsley, 1996; Friesen & Kuskis, 2013; Picciano, 2001; Salmon, 2002, 2004; Scardamalia & Bereiter, 2006; Sherry, 1995). Additionally, effective interpersonal interaction can enhance students' sense of "social presence"—the degree to which a person is perceived as a "real person" in mediated communication—and thereby support students' psychological connection to the course (e.g., Gunawardena & Zittle, 1997; Shearer, 2013; Short, Williams, & Christie, 1976; Young, 2006). One meta-analysis examining studies of interaction in online learning environments concluded that increased interpersonal interaction, either with the instructor or other peers, positively affects student learning (Bernard et al., 2009). Among the many possible paired interaction combinations, learner–instructor interactions have been found to be the most significant factor in predicting perceived learning outcomes in online environments (Fredericksen, Pickett, Shea, Pelz, & Swan, 2000; Jiang & Ting, 1999; Swan et al., 2000).

Learners' perceptions of the quality of learner–instructor interactions are also an important predictor of learners' overall satisfaction in an online learning environment (Kang & Im, 2013).

Unfortunately, it is particularly challenging to implement effective interpersonal interactions in an online course. The distance created by online learning environments detracts from a sense of social belonging while also creating a sense of isolation, frustration, and boredom (Berge, 1999; Hara, 2000; Northrup, 2002; Young, 2006). In turn, the lack of peer and learner–instructor interactions can impact students' motivation and cognitive processes (Schunk, Pintrich, & Meece, 2008). To address the lack of interactivity in an online learning environment, researchers consistently agree that online instructors need to pay special attention to facilitate interactions in an online learning environment (An, Shin, & Lim, 2009; Berge, 1999; Cho & Cho, 2016; Cho & Kim, 2013; Hew, Cheung, & Ng, 2010; Mandernach, Forrest, Babutzke, & Manker, 2009; Moore, 1989).

Among the many forms that interpersonal interaction can take in an online learning environment (Chou, 2003), email is one such interpersonal communication mode that the instructor can actively initiate. Although instructor emails are widely used across online courses, they have been found to vary substantially in length, meaningfulness, and frequency (Hassini, 2006), which in turn may have different influences on the interactivity of the online learning environment. In a recent study that links online course design features with student learning outcomes from 23 high-volume lower division online college courses (Jaggars & Xu, 2016), for example, the researchers found that "high-interaction instructors posted announcements on a regular basis to remind students about requirements for assignments, coming deadlines, newly posted documents, examinations, and other logistic issues" (p. 278), and that such high interaction

is positively related to student learning outcomes. In contrast, in courses where the instructor posted announcements and reminders to students on a limited basis, students were more likely to express dissatisfaction with the course.

Another means of increasing interpersonal interaction is by providing synchronous communication opportunities, especially through in-person interactions. This often takes place through in-person office hours, which have been seen as an opportunity for help seeking outside of the classroom (Acitelli, Black, & Axelson, 2003). However, existing studies suggest that office hour visits are generally brief and underutilized (Bippus, Kearney, Plax, & Brooks, 2003; Griffin et al., 2014; Jaasma & Koper, 1999; Nadler & Nadler, 2000), which is partly due to students' discomfort in one-on-one conversations with the course instructor. Based on these concerns, some educators have recommended alternatives that would increase the chances of making use of in-person discussions, such as structured topical office hours and group discussion sections (e.g., Weimer, 2015). Despite these theoretical discussions, the use and possible impact of a voluntary group meeting time for answering student questions in a fully online course has not yet been empirically examined.

The current study addresses this literature gap by examining student performance in a fully online math course taught under two conditions: (1) a control condition with minimal numbers of instructor emails and no reserved classroom space for in-person meetings and (2) a treatment condition with more frequent instructor whole class communications and a weekly one-hour in-person meeting time for answering student questions. Though all students were highly encouraged to attend the in-person meeting, record of attendance was not kept, and students were not penalized for skipping the meetings. As such, the in-person discussion section was completely voluntary and was comparable to other voluntary in-person interaction opportunities, such as office hours.

Methods

Research Context

This study examines a precalculus course taught at a large public four-year university in the western United States. The precalculus course is a prerequisite for calculus, which is generally required across all STEM-related majors. Students who need to take calculus can skip the precalculus course by scoring at least a 3 on the Advanced Placement Calculus exams, scoring at least 600 on the SAT Math portion, or passing a placement exam. Overall, about 350 students, three percent of the incoming freshman class, take precalculus in their first year.

Two years of data are included in the analysis, starting from the 2012–2013 academic year through the 2013–2014 academic year. The data for this study comes from two sources: the Office of Institutional Research (OIR) and the online instructional system used in the course, ALEKS. The OIR dataset includes information about students' academic and demographic background, such as students' final grade in the course, SAT scores, major, year of initial enrollment, gender, and ethnicity. The ALEKS dataset contains students' initial assessment score in precalculus, instructor emails, and final exam score with details for each question in the exam.

Prior to the fall of 2012, precalculus was offered through a blended delivery format with three 1-hour, in-person lectures in a physical classroom per week in conjunction with online ALEKS tutorials. Starting in the fall of 2012, however, the university converted precalculus into a fully online course taught through ALEKS; students did not physically meet for lectures and instead worked individually through the ALEKS instructional system. In both years included in

our study, the course used the same syllabus, online learning materials, and the same set of test banks for the final exam.

The initial assessment is an adaptive questioning system that pulls items from a test bank on ALEKS. It gauges each student's content knowledge upon initial login. Following the initial assessment, ALEKS determines lessons that the student has already mastered and has yet to master. Throughout the school term, students work individually on topics that they have yet to master. ALEKS adapts its suggested topics, grouped into larger categories, for the students to work on based on the students' recent progress. Since students worked on ALEKS individually and at different paces, the instructor held more of a support role in answering student questions as they arose and enforcing deadlines for topic categories in ALEKS.

Across all terms in this study, students took their final exam on ALEKS. A total of 40 different question items were randomly generated on ALEKS, though the school's math department was able to predetermine which topic would be tested in each question item. All the exam questions were randomly drawn from ALEKS' test bank based on the predetermined composition of topics. The specific set of topics covered during the final exam changed slightly between the two academic years. However, for a particular topic (such as "Double-Angle Identities"), students taking the course in different terms were subject to the same test bank. A total of 26 questions out of 40 tested were drawn from the same topics across the four terms included in our study.

Precalculus was only offered during the fall and winter quarters, and a total of 1,485 students were enrolled in precalculus across the four academic school terms. We limited the analysis to 1,003 first-time and nontransfer enrollees in precalculus and additionally excluded 40 students who were missing information on key demographic variables. The final analytic sample consists of 963 students. Enrollment counts by term can be found in Table 1.

Table 1
Enrollment Counts by Term

	In-Person Support	Total	Analysis Sample
Fall 2012	No	503	328
Winter 2013	No	330	177
Fall 2013	Yes	417	310
Winter 2014	Yes	235	148
Total		1,485	963

Course Format Description

Online with low interactivity (control condition). The precalculus course with low interactivity (referred to as the *OLI course* or *control group* hereafter) was offered in the 2012–2013 academic year. Two course sections, each taught by a different instructor, were offered during fall 2012. Only one section was taught during the winter 2013 term, and it was taught by one of the instructors from the fall 2012 term. Instructors were available throughout the week in both in- person and online office hours. Instructors answered individual student emails but also initiated whole-class emails. While students could find key information on the course web page, the instructor used the whole-class emails to serve as a means to proactively communicate with students and keep them on track. Column 1 in Table 2 summarizes the frequency of whole-class

instructor emails and breaks down these emails by their primary purpose. On average, the three sections had 2.77 instructor-initiated emails to the whole class per week. The majority of these emails were either about office hours (38.55%) or course logistics (36.14%), including one or two welcome emails per section. Only 2.41% of the emails were about the course content. The remaining emails were either about the exams (14.46% for the midterm and 6.02% for the final) or reminders (2.41%).

Table 2
Instructor-Initiated Emails by Content

	OLI, 2012–13 (%)	OHI, 2013–14 (%)
Logistics and Welcome	36.14	34.25
Office Hours	38.55	12.71
Reminders	2.41	19.89
Content	2.41	7.73
Midterm Related	6.02	5.52
Final Exam Related	14.46	7.73
Discussion Section	-	17.13
Average # Emails Per Week	2.77	6.25

It is worth noting that the grading scheme varied slightly between fall and winter terms. In fall 2012, the midterm and final exam were worth 30% and 40% of students' grades, respectively. The remaining 30% was based on one office hour attendance (2%) and four ALEKS milestones, each worth 7% of the final grade. In winter 2013, the department modified the grading scheme of the precalculus course. The midterm and final exam were worth 25% and 40%, respectively. The course additionally had six milestones (4% each), four quizzes (2% each), and an orientation quiz (3%). With the exception of shorter intervals between milestones and the incorporation of online quizzes, the winter 2013 precalculus offering was similar to fall 2012 in students' amount of contact with the instructor.

Online with high interactivity (treatment condition). The sections offered during the 2013–2014 academic year were nearly identical to the winter 2013 precalculus offerings, with each of the 10-week courses outlined the same as the winter OLI course. Quizzes and milestones were also due on the same week numbers. The grading scheme was also the same as that of the winter 2013 section. However, there were two primary differences between the online with high interactivity course (referred to as *OHI course* or *treatment group* hereafter) and the OLI course.

First, an hour classroom time was reserved weekly for students to voluntarily meet in a physical lecture hall with the instructor (referred to as *discussion section* hereafter). The lecture hall had room for over 300 students, which was well over the enrollment count. Students were encouraged to submit questions prior to the discussion section through emails with regard to the course materials covered during that week. The instructor used the physical classroom meeting time to answer student questions that were either collected through emails or raised during the discussion section. The discussion section was completely voluntary, and students were not required to attend the session. According to the course instructors, the majority of the students attended the first session, but the attendance rate declined to around 25% afterward. The weekly 25% attendance rate is, nevertheless, substantially higher than the typical usage of instructors' office hours in either the OLI or OHI conditions.

Second, the two instructors who taught during the fall 2013 term were different from the instructors who taught during the 2012–2013 academic year. One of the instructors who taught during the fall 2013 term also taught during the winter 2014 term. However, since the course structure was predetermined by the department with an online work schedule and materials that were identical to those of the winter 2012–2013 term, each instructor’s predominant influence on the course took place through email communication and the physical classroom meetings. Whole-class emails for the OHI sections were sent much more frequently, averaging 6.25 times a week, which is more than twice as frequent as the instructor-initiated emails in the OLI condition.

Column 2 in Table 2 further breaks down the emails sent to the whole class by their content. It is worth noting that due to the higher frequency of emails overall, the OHI condition outnumbered the OLI condition almost in every type of email except for office hours. Hence, below we focus on the proportion of different types of emails to shed light on whether the instructors also differed in their focus in sending these emails between the two years.

Similar to the OLI courses, a large proportion of the instructor-initiated emails in the OHI condition were also about course logistics (34.25%). Probably due to the additional discussion sections, there were proportionately fewer emails about office hours than the OLI condition (12.71%), but a substantial proportion of emails about the discussion section (17.13%). The most striking differences between the OLI and OHI conditions lie in reminders and content-related emails. Compared to the OLI condition, the OHI conditions proportionately sent 8 times more reminder emails (2.41% vs. 19.89%). These emails were sent on a weekly regular basis, mainly to keep students on track. There was also a substantially larger proportion of course-content-related emails sent in the OHI condition (7.73% vs. 2.41%), a handful of which included example problems.

Methods

Outcome Measures

We examined the impact of OHI relative to OLI on student performance through two outcome measures: a final exam subscore calculated from overlapping topics tested in all four terms and final course grade.

The full final exam consisted of 40 question items. The actual questions posed varied from student to student, but all were randomly generated on ALEKS from a set of question banks. Each question bank corresponded to a course topic. However, as mentioned above, the specific set of topics covered during the final exam changed slightly across terms. One potential problem associated with such term-by-term variations was that the final exam score might not have been directly comparable across terms due to different sets of topics covered during the exam. For example, if the topics selected by the department in 2013 tended to be slightly easier than those in 2012, the average difference in the final exam score may have actually reflected the difficulty of the exam rather than learning outcomes.

To enable fair comparisons across terms, we examined the final exam subscore as a percentage score (points earned divided by total points possible). The final exam subscore was calculated from using only question topics covered across all four quarters. As a robustness check, we used the raw final exam score and found fairly similar results. Since the same question bank was used for particular topics, such as “Double-Angle Identities,” students’ scores for that topic

were directly comparable across terms. A total of 26 questions out of 40 tested were drawn from the same topics across the four terms. As such, only 26 items were included in the calculation of the final exam subscore.

We additionally examined course grades, as they were an important reflection of each student's overall success in a course. We looked particularly at the grades from winter 2012 and after, since the grading schemes and weight distribution were the same across these three terms. We converted course letter grades to a 4-point numeric scale. The grades B- and B+, for example, equated to 2.7 and 3.3 grade points, respectively. The grade F equated to 0 grade points. We used 4.3 to represent A+ in order to distinguish the higher valued A grade, even though the school calculates both A+ and A as 4 grade points. A small number of students ($n = 58$) took precalculus on a pass/no pass grading scale. These students were included in our primary analysis, where a "pass" grade equated to 2 grade points (the equivalent of a C) and a "no pass" grade equated to 0 grade points. In a separate robustness check, we also excluded these students from the sample, and the results remained the same.

Propensity Score Matching (PSM)

One advantage of this dataset is that only one condition (OLI or OHI) was offered at a time. Students could only self-select into a different course format if they delayed taking precalculus for a different year. However, this decision was unlikely to happen because the course was a prerequisite to many STEM courses. Since many of the courses were sequence courses and also had calculus as further prerequisites, postponing the precalculus course could greatly delay graduation. Furthermore, students were not guaranteed a different instructional format if they delayed taking precalculus because they did not know what format future courses would be taught in. The remaining concern, therefore, would be possible variations between cohorts in student characteristics.

Specifically, although only one treatment condition was offered during a particular term, which minimized potential self-selection, we were still concerned that the composition of student demographics and abilities might have been different between the OLI and the OHI groups. Although the raw comparison between the two groups presented in Table 3 (mean differences based on the "unmatched" sample) indicated that the students taking the course in the 2013–2014 school year (the OHI group) had similar initial ALEKS assessment scores compared to students taking the course in the 2012–2013 school year (the OLI group), some other significant differences emerged across the two groups. For example, the OHI group had significantly lower SAT scores and also had a higher proportion of students who declared in majors that required math courses. This was partly due to the fact that during the past few years, the university where this study was conducted had been steadily increasing enrollment of state residents and lowering admission criteria, especially in STEM-related fields. As a result, this led to disproportionate increases in the fraction of at-risk students being accepted to campuses and STEM-related fields.

Table 3
Pooled PSM Balance Check for Fall and Winter Students

Mean		Standard Deviation					
		OLI 2012-13	OHI 2013-14	Diff.	OLI 2012-13	OHI 2013-14	Ratio
Initial Assessment	Unmatched	23.45	24.19	-0.05	14.82	15.84	0.94
	Matched	21.53	21.16	0.03	9.73	9.09	1.07
SAT Math Score	Unmatched	-0.69	-0.80	0.20	0.54	0.72	0.76
	Matched	-0.72	-0.76	0.07	0.48	0.49	0.99
SAT Verbal Score	Unmatched	-0.86	-1.05	0.27	0.72	0.85	0.84
	Matched	-0.93	-0.99	0.08	0.60	0.62	0.96
Female	Unmatched	0.62	0.61	0.03	0.49	0.49	0.99
	Matched	0.65	0.65	0.00	0.48	0.48	1.00
Ethnicity							
Asian	Unmatched	0.26	0.31	-0.11	0.44	0.46	0.95
	Matched	0.27	0.27	0.00	0.45	0.45	1.00
Black	Unmatched	0.05	0.05	0.01	0.22	0.21	1.03
	Matched	0.02	0.02	0.00	0.15	0.15	1.00
Hispanic	Unmatched	0.48	0.45	0.06	0.50	0.50	1.00
	Matched	0.59	0.59	0.00	0.49	0.49	1.00
White	Unmatched	0.11	0.11	-0.01	0.31	0.32	0.99
	Matched	0.08	0.08	0.00	0.27	0.27	1.00
Other	Unmatched	0.10	0.08	0.07	0.30	0.27	1.11
	Matched	0.04	0.04	0.00	0.20	0.20	1.00
Major Requires Math	Unmatched	0.42	0.58	-0.31	0.49	0.49	1.00
	Matched	0.44	0.44	0.00	0.50	0.50	1.00
Freshman	Unmatched	0.81	0.78	0.09	0.39	0.42	0.94
	Matched	0.87	0.87	0.00	0.33	0.33	1.00

Note. "Matched" shows the matched estimates using Mahalanobis distances and kernel matching with a bandwidth of 1.5. Students in the treatment group received in-person support while students in the control group did not. SAT Math and Verbal scores are centered at a score of 600 (the cutoff score for students who would like to skip to the next math course) and have been divided by 100.

To address baseline differences between students taking the course in different terms, we used a propensity score matching (PSM) strategy to generate two comparable groups by selecting similar students in each condition. Specifically, we chose students from the OLI group who resembled students from the OHI group based on all observable demographic and ability characteristics and then discarded dissimilar OLI students who failed to be matched to an OHI student.

PSM is a two-step process that involves first mapping a series of covariates onto a unidimensional value (a propensity score) that represents the probability of being in the OHI group or not. For this first step, we used logistic regression to calculate each individual's propensity score. Based on the consideration that there may have been differences in student characteristics based on the term that they take precalculus (e.g., weaker students may hold off on taking

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precalculus until winter), we estimated the logistic regressions on the fall cohorts and winter cohorts separately and matched fall students to fall students and winter students to winter students only. The results from the logistic regression estimation of students' probability of being in the OHI condition are presented in Table 4. In the second step, propensity scores for each person in the two groups were matched so that the treatment and control groups were similar. We used Mahalanobis distances and kernel matching with a bandwidth of 1.5 and with replacement.

Table 4
Logistic Regression for OHI Enrollment Propensity Score

	Fall Terms	Winter Terms
Initial Assessment	-0.01 (0.03)	-0.00 (0.04)
Sqrt(Initial Assessment)	0.03 (0.28)	-0.03 (0.44)
SAT Math Score	0.17 (0.16)	0.55* (0.25)
SAT Verbal Score	0.22+ (0.12)	0.55** (0.18)
Female	0.12 (0.17)	0.16 (0.26)
Ethnicity		
Asian	-0.20 (0.29)	0.32 (0.45)
Black	0.20 (0.45)	0.80 (0.65)
Hispanic	0.31 (0.27)	0.51 (0.45)
Other	0.69+ (0.39)	-0.03 (0.62)
Major Requires Math	-0.85*** (0.17)	-0.29 (0.24)
Freshman	0.58** (0.21)	-0.10 (0.30)
Constant	0.14 (0.77)	0.66 (1.21)
<i>N</i>	638	325

Note. Standard errors in parentheses. “White” is the base case for ethnicity. SAT Math and Verbal scores are centered at a score of 600 and have been divided by 100.

+ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Covariates for matching included initial assessment score, SAT Math and Verbal scores, gender, ethnicity, whether the student declared a major that requires math, and whether the student was in his or her first year at the university. Some researchers (e.g., Austin, 2011) suggested adding nonlinear terms of covariates to achieve balance in the standard deviation given that the purpose of PSM was to achieve balance in the entire distribution of baseline covariates. We included the square root of initial assessment score since students with low scores had a lot of room for improvement, while students with high scores only needed to go over a few concepts.

The comparison between the OLI and OHI conditions based on the matched sample in Table 3 indicated that the two groups were fairly balanced in terms of both means and standard deviation of all the key variables: specifically, we used the standardized difference—calculated as the absolute difference in each variable’s mean across the OLI and OHI groups and divided by the pooled standard deviation of the variable—to assess the difference in means between the treatment and control group. For the standard deviations, we found the standard deviation ratio for each variable, computed as the ratio of the OLI group standard deviation to the OHI group standard deviation. As shown in Table 3, the OHI and OLI groups were fairly balanced, with a standardized difference of at most 0.1 and a standard deviation ratio between 0.8 and 1.25. We also checked the balance for the subsample of students who took precalculus during the fall terms and winter terms, respectively. The results for the balance checks are presented in Appendix Tables 1 and 2, and are fairly similar to those presented in Table 3.

The balance achieved through PSM procedures was also reflected in the overall distribution of scores in each term. Figure 1 shows the kernel density plots of the pre- versus postmatch distributions of the propensity scores for the OHI and OLI groups in fall term and winter term, respectively. Both terms had an overlapping region of common support between the OLI and OHI conditions, and the distributions between OLI and OHI students became almost identical after matching. These results, therefore, justified the comparisons between the OLI and OHI conditions based on the matched sample.

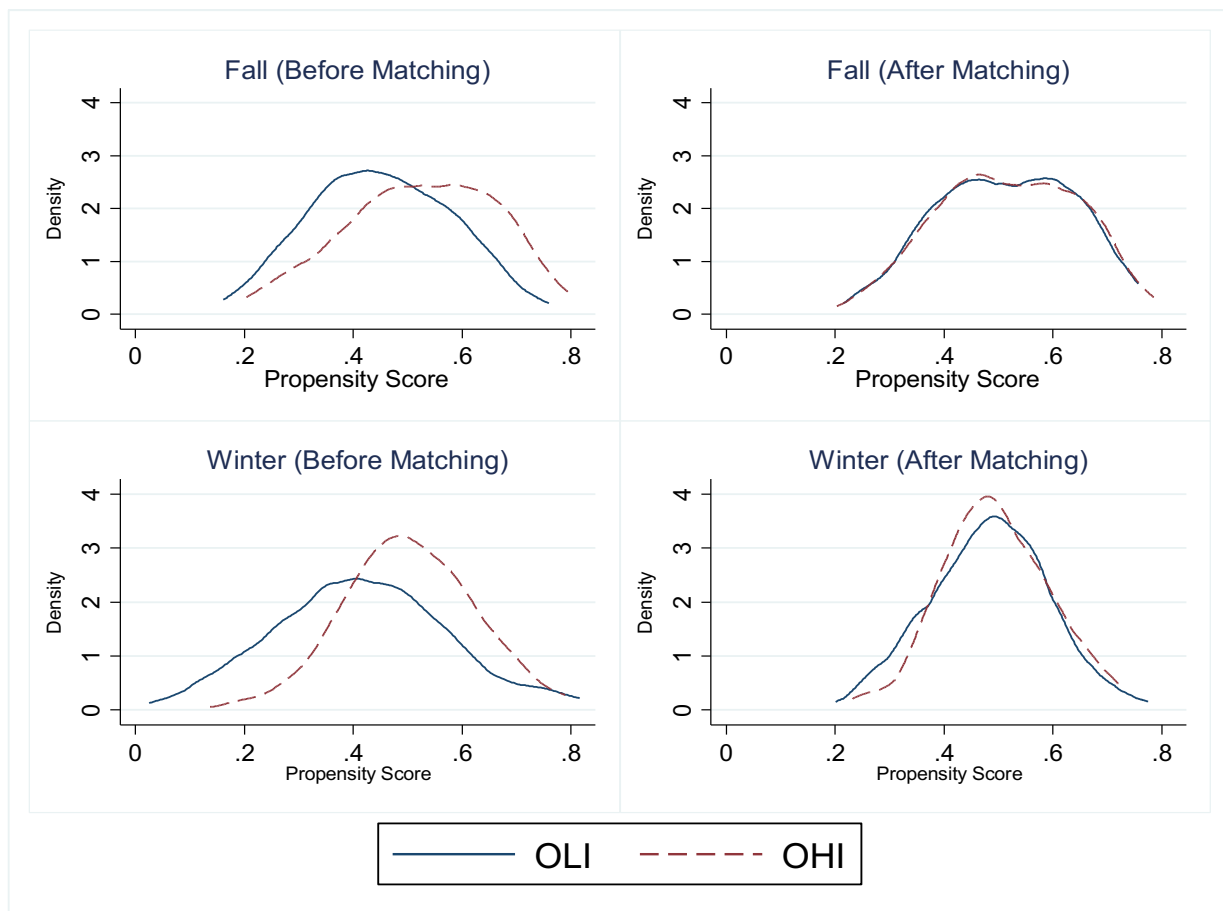


Figure 1. Propensity score pre- and postmatch distribution.

Finally, although we were able to achieve balance in terms of observable student characteristics, we were still concerned that our models might face the threat of missing variable bias. We therefore used Rosenbaum’s sensitivity analysis (Rosenbaum, 2005) to examine the magnitude of the missing variable needed to negate our results.

Results

Figure 2 shows the grade distribution in each instructional condition. Overall, the OHI students had a higher final exam subscore (70.35%) than the OLI students (64.96%). Table 5 presents the estimated treatment effects of providing high-level interactivity (OHI) in the precalculus course on student final exam scores based on test items drawn from the same test bank. Column 1 presents estimated effect of OHI based on the matched sample across all the four terms; Column 2 and Column 3 focus on the fall and winter terms, respectively, to address the possibility that the impact might be different on the fall and winter cohorts. Finally, Column 4 presents estimates based on the pooled sample again but includes additional interaction terms between OHI and a dummy variable indicating whether the term is winter quarter (versus fall quarter).

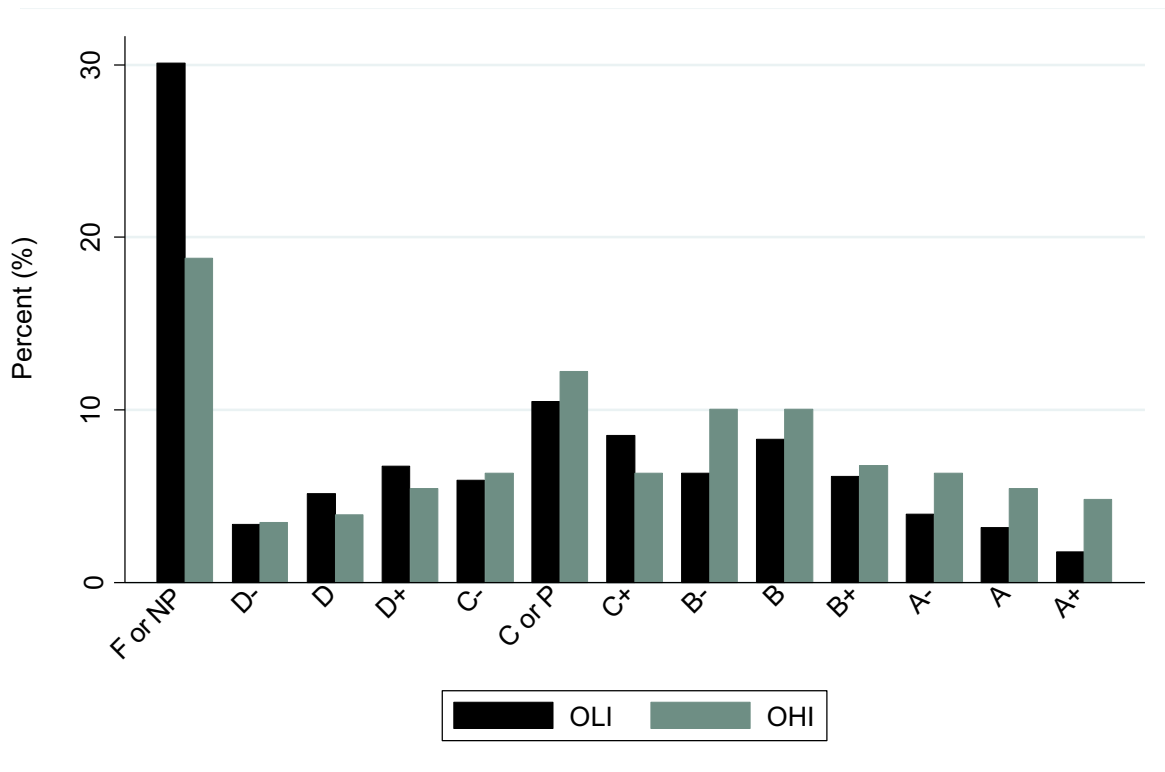


Figure 2. Grade distribution for OLI and OHI conditions.

Table 5

OHI Treatment Effect on Total Final Exam Subscore

	M1	M2	M3	M4
	Full Sample	Fall Only	Winter Only	Full Sample
OHI	4.11** (1.45)	4.17* (1.78)	4.17+ (2.49)	4.11* (1.77)
Winter	2.54+ (1.50)			2.55 (2.09)
OHI × Winter				-0.03
R-squared	0.17	0.17	0.20	0.17
N	553	388	165	553

Note. Standard errors in parentheses. Models include weights from propensity score matching. M1 and M4 include both fall and winter samples.
+ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Overall, all models consistently show that the high number of interpersonal interactions increased students' final exam scores, as measured by total points correctly answered divided by total points possible. Focusing on the estimates based on the pooled sample presented in Column 1, taking the course through the OHI condition was significantly associated with a higher score by more than four percentage points, which is equivalent to an effect size of 0.22 standard deviations. The effect of OHI was also significant, with similar effect size when estimated based on the fall (Column 2) and winter samples (Column 3) separately.

Table 6 further presents the estimated effects of OHI on final course grades using the same model specifications presented in Table 5. Results based on the pooled sample shown in M1 indicate that students in the OHI condition received a final grade that was 0.44 grade points higher than their counterparts in the OLI condition, which is approximately equal to an increase from C- to C. Students needed to receive a C or above in order to pass the precalculus course. In the OLI condition, approximately 6% of the students received a C-. The benefit of the improved interpersonal condition, given its effect size, may, hence, particularly benefit students on the margin of passing the course. We also examine the extent to which OHI improves the course completion rate, where students need to receive a C or above in order to pass the precalculus course. Raw comparisons between the two conditions indicate that the OHI group had a much higher course passing rate (62% vs. 49%). Subsequent model-adjusted estimation using course passing rate as the outcome based on the full sample (M5 in Table 6) yielded an effect of 0.19, indicating that the OHI condition improved the average probability of passing the precalculus course by 19 percentage points

Table 6

OHI Treatment Effect on Grade Points and Passing

	M1	M2	M3	M4	M5
Full Grades	Fall Grades		Winter Grades	Full Grades	Full Pass Rate
OHI	0.44*** (0.11)	0.49*** (0.13)	0.31 (0.22)	0.49*** (0.13)	0.19*** (0.05)
Winter	0.22+ (0.13)			0.31+ (0.19)	0.21** (0.07)
OHI × Winter				-0.18 (0.25)	-0.14 (0.10)
<i>R</i> -squared	0.24	0.24	0.24	0.24	0.21
<i>N</i>	553	388	165	553	553

Note. Standard errors in parentheses. Grade points are calculated on a 4.0 scale. Models include weights from propensity score matching. M1, M4, and M5 include both fall and winter samples. Grade points is the outcome measure in M1 to M4. Pass (C grades or higher coded as 1) or no pass (below C coded as 0) is the outcome measure in M5.

+ $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Although the results shown so far indicate that students are fairly balanced based on the matched sample, it is still possible that there might be unobserved differences between the OLI and OHI groups that are also correlated with student course performance. It is worth noting that the descriptive differences between the OLI and OHI students on observable characteristics indicate that the OHI groups are likely to be lower performing students due to the college-wide policy of lowering admission criteria during the period of this study; this indicates that our current estimate is likely to actually underestimate the positive effect of the OHI condition on student learning outcomes.

That said, we also formally addressed the omitted variable problem by using Rosenbaum's sensitivity analysis (2005) to estimate how large the hidden bias would need to be to overthrow our results. The results indicated that the confidence interval would include 0 in the presence of an upward hidden bias of 5 for both outcome measures; that is, to question our conclusion regarding the positive association between OHI and student course performance, an unobserved covariate would have to be positively associated with student course performance while increasing the odds of receiving OHI by a factor of five. This effect size is dramatically larger than the association between any of the observed student characteristics and the odds of receiving OHI presented in Table 4, indicating that the current conclusion is extremely robust against potential unobserved covariates.

Discussion

Online expansion has already become an unstoppable trend in higher education, with an estimated 5–7 million students now enrolling in at least one online course each year. Yet, existing studies have typically found that students do not perform as well in an online course as in a traditional in-person learning environment, particularly among less privileged student populations.

Despite the consensus and urgent need to improve online course effectiveness and student learning outcomes, colleges are faced with a wide and often vague array of recommended online instructional practices with rather limited evidence regarding the benefits of each specific strategy.

In the current study, we describe a specific policy change in a large entry-level college online precalculus course using an adaptive learning system where two practices were implemented in later years to increase interpersonal interactivity: (1) whole-class instructor emails that were sent on a regular basis to keep students on track and (2) a voluntary weekly meeting time in a physical classroom for students to raise content-related questions. Based on a sample of similar students, we found that these practices that intend to increase the interactivity of the course brought about substantial benefits to students. Specifically, students in the higher interactivity condition scored four percentage points higher on their course final exam than students who did not receive the same kind of treatment. The higher level of interpersonal interaction also helped boost student final grades up by almost half a grade.

The effect size of half a letter grade is substantial, considering that almost 13% of students enrolled in the traditional OLI condition received either a C- or D+ and were therefore on the margin of passing the course (where the threshold is C or above). Indeed, our analyses on course passing rate indicated that the increased interpersonal interactivity offered in the OHI condition significantly improved course passing rate by 19 percentage points. Since the requirement of retaking precalculus would delay students' enrollment in calculus, the positive impact of OHI on course passing rate is somewhat more consistent with the notion of a threshold or "tipping point" in how a greater level of interpersonal interactivity in a fully online learning environment affects academic progress.

Limitations

Despite these promising findings, this study also faced several limitations, including the lack of random assignment and the one-year time span of each condition reflected in the data. Although our results indicate that students were fairly balanced based on the matched sample, and the current conclusion is extremely robust against potential unobserved covariates, we cannot rule out the possibility that other time-variant factors might have at least partially contributed to the positive student outcomes observed in later terms. Moreover, the data used in this analysis reflects only a one-year time span for each condition. While the results hold from fall to winter, we were unable to test whether the results were consistent from year to year, whether the findings extended in the same way to later years, and whether subsequent courses were impacted in a similar way. Since the two formats did not have the same instructor across both years in this study, we also cannot confirm whether or not instructor-level factors, such as personality, reputation, and teaching experience, impacted student outcomes. However, instructor influence is reasonably limited since most of the learning took place through the automated online learning system. Nevertheless, it is desirable for future studies to use a completely randomized design to provide experimental evidence regarding the impacts of these practices, both in current and subsequent course outcomes.

Finally, according to the instructor, less than half of the students in the OHI condition attended the weekly meetings in the physical classroom. Furthermore, no record was kept regarding attendance at the meetings, limiting our ability to identify students who ever attended these sessions and the average frequency of attendance. As such, the estimated effect presented in this study represents an average intent-to-treat effect, which may underestimate the actual impact of participating in these weekly meetings on learning outcomes. The data available to us does not

record which individual students attended the weekly discussion sections, nor does the data contain the characteristics of attending students. Future studies with more detailed student participation records may wish to examine which type of students benefit the most from these voluntary in-person discussion sections. Finally, the majority of the students in our sample lived either on campus or close to campus. As such, students were all within physical distance to attend the in-person meetings. Therefore, the results from the current study may not speak to other online courses where in-person meetings are a significant challenge to students.

Although more research is needed to shed more light on the best practices for teaching an online course, the findings from our study provide important empirical evidence that the effectiveness of semester-long college courses with a high volume of enrollment can be substantially improved through well-structured activities to increase interpersonal interactions. Therefore, colleges that are either currently offering online courses or contemplating replacing in-person courses with online learning may consider implementing similar practices in their online courses. Campuses that cannot provide in-person support in the form of a weekly large lecture meeting (due to space or cost constraints) may want to experiment with other types of support that closely approximate it, such as synchronous online meetings, small group in-person meetings, or targeted-group interventions.

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Appendix A

Table A1

PSM Balance Check for Fall Students

Variable		Mean			Standard Deviation		
		2013–14	2012–13	Diff.	2013–14	2012–13	Ratio
Initial Assessment	Unmatched	24.48	23.62	-0.06	15.93	14.95	0.94
	Matched	21.00	21.53	0.04	8.97	9.83	1.09
SAT Math Score	Unmatched	-0.74	-0.70	0.07	0.70	0.57	0.81
	Matched	-0.78	-0.74	0.07	0.49	0.51	1.04
SAT Verbal Score	Unmatched	-1.01	-0.92	0.13	0.87	0.74	0.84
	Matched	-1.02	-0.97	0.08	0.64	0.62	0.97
Female	Unmatched	0.57	0.58	0.02	0.50	0.49	1.00
	Matched	0.59	0.59	0.00	0.49	0.49	1.00
Ethnicity							
Asian	Unmatched	0.32	0.23	-0.20	0.47	0.42	0.91
	Matched	0.26	0.26	0.00	0.44	0.44	1.00
Black	Unmatched	0.05	0.05	-0.02	0.22	0.21	0.96
	Matched	0.02	0.02	0.00	0.14	0.14	1.00
Hispanic	Unmatched	0.44	0.48	0.10	0.50	0.50	1.01
	Matched	0.59	0.59	0.00	0.49	0.49	1.00
White	Unmatched	0.13	0.12	-0.03	0.33	0.32	0.97
	Matched	0.08	0.08	0.00	0.27	0.27	1.00
Other	Unmatched	0.07	0.12	0.15	0.26	0.33	1.26
	Matched	0.05	0.05	0.00	0.21	0.21	1.00
Major Requires Math	Unmatched	0.60	0.40	-0.40	0.49	0.49	1.00
	Matched	0.43	0.43	0.00	0.50	0.50	1.00
Freshman	Unmatched	0.76	0.83	0.20	0.43	0.37	0.87
	Matched	0.88	0.88	0.00	0.33	0.33	1.00

Note. “Matched” shows the matched estimates using Mahalanobis distances and kernel matching with a bandwidth of 1.5. Students in the treatment group received face-to-face support while students in the control group did not. SAT Math and Verbal scores are centered at a score of 600 (the cutoff score for students who would like to skip to the next math course) and have been divided by 100.

Increasing Interpersonal Interactions in an Online Course: Does Increased Instructor Email Activity
and Voluntary Meeting Time in a Physical Classroom Facilitate Student Learning?

Table A2

PSM Balance Check for Winter Students

Variable		Mean			Standard Deviation		
		2013–14	2012–13	Diff.	2013–14	2012–13	Ratio
Initial Assessment	Unmatched	23.65	23.08	-0.04	15.72	14.59	0.93
	Matched	21.58	21.54	0.00	9.45	9.52	1.01
SAT Math Score	Unmatched	-0.92	-0.67	0.52	0.73	0.48	0.66
	Matched	-0.70	-0.67	0.06	0.47	0.39	0.82
SAT Verbal Score	Unmatched	-1.13	-0.73	0.59	0.81	0.66	0.82
	Matched	-0.89	-0.84	0.08	0.54	0.50	0.93
Female	Unmatched	0.68	0.72	0.09	0.47	0.45	0.97
	Matched	0.80	0.80	0.00	0.40	0.40	1.00
Ethnicity							
Asian	Unmatched	0.29	0.32	0.05	0.46	0.47	1.02
	Matched	0.29	0.29	0.00	0.46	0.46	1.00
Black	Unmatched	0.05	0.06	0.07	0.21	0.24	1.15
	Matched	0.03	0.03	0.00	0.16	0.16	1.00
Hispanic	Unmatched	0.48	0.47	-0.01	0.50	0.50	1.00
	Matched	0.58	0.58	0.00	0.50	0.50	1.00
White	Unmatched	0.09	0.10	0.01	0.29	0.29	1.02
	Matched	0.08	0.08	0.00	0.27	0.27	1.00
Other	Unmatched	0.09	0.05	-0.16	0.29	0.23	0.79
	Matched	0.03	0.03	0.00	0.16	0.16	1.00
Major Requires Math	Unmatched	0.54	0.47	-0.15	0.50	0.50	1.00
	Matched	0.47	0.47	0.00	0.50	0.50	1.00
Freshman	Unmatched	0.81	0.77	-0.10	0.39	0.42	1.08
	Matched	0.87	0.87	0.00	0.34	0.34	1.00

Note. “Matched” shows the matched estimates using Mahalanobis distances and kernel matching with a bandwidth of 1.5. Students in the treatment group received face-to-face support while students in the control group did not. SAT Math and Verbal scores are centered at a score of 600 (the cutoff score for students who would like to skip to the next math course) and have been divided by 100.