ACADEMIC ACHIEVEMENT AND PERSISTENCE

IN ONLINE SELF-PACED COURSES

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by

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The undersigned, appointed by the dean of the Graduate School, have examined the

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IN ONLINE SELF-PACED COURSES

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and hereby certify that, in their opinion, it is worthy of acceptance.

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DEDICATION

I would like to thank God and my family for all of their support during my time of coursework and dissertation, especially my husband, Dave, for his unwavering support. I would like to thank my parents, especially my mother, for teaching by example. Thank you to my amazing children, Michelle and David, for their love and encouragement, and a special thank you to my wonderful grandchildren, Gabrielle and Isabelle, for being such a blessing!

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ACADEMIC ACHIEVEMENT AND PERSISTENCE

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ABSTRACT

This study focused on building achievement and persistence models of students enrolled in online self-paced courses using 11,829 AY 2014-15 records from the University of Missouri. Course satisfaction, delivery mode, and student characteristics were used to create the models. Model building and trimming using hierarchical linear modeling occurred in which level-2 units were online self-paced courses and level-1 units were students. In terms of persistence, the log-odds of persistence were related to course satisfaction holding constant other predictors. Gender, academic level, enrollment time, and active completion time had significant effects on persistence and achievement. Persistence and prior self-paced experience also had significant effects on achievement, with prior self-paced course experience having a negative effect. Enrollment time had negative effects on persistence and achievement. Females and upper-division students generally received higher scores than males and lower-division students. The effect of persistence on achievement was largest by far, as one might logically predict.

Academic Achievement and Persistence

Chapter One

As is evident by enrollment trends, distance education continues to experience unprecedented growth. The U.S. Department of Education reported that in fall 2014 at Title IV institutions, 4,862,519 undergraduate students, or 27.4% of the total number of undergraduate students at those institutions, enrolled in distance education courses, with 11.9% enrolling exclusively in distance education courses; 966,307 graduate-level students, or 33.1% of the total number of graduate students at those institutions, also enrolled in distance education coursework, with 25.2% enrolled exclusively in distance education courses (Allen & Seaman, 2016; Ginder, Kelly-Reid, & Mann, 2015; Poulin & Strout, 2016). About 69% of the 2- and 4-year postsecondary degree-granting institutions in the United States offered distance education courses in fall 2014 with a total of 5.8 million students, or 28% of the total number of students at those institutions, enrolled in distance education courses in fall 2014 (Allen & Seaman, 2016; Ginder et al., 2015).

For comparison, in 2000-01, about half of those institutions offered distance education courses, for a total of 2.9 million enrollments in university-level coursework (Waits & Lewis, 2003). Postsecondary institutions may be increasing online course offerings in response to dwindling budgets, the economy, and such initiatives as massive open online courses offered for free or at a nominal cost by a growing number of organizations, with some institutions beginning to grant credit for those courses if

students obtain a certificate and pass a proctored exam (DeSantis, 2014; Mintz, 2013; Young, 2013).

Postsecondary schools indicate the primary reasons they provide distance education courses are to help students build flexibility into their schedules, provide access for those who could not participate otherwise, increase course availability, and increase enrollment (Parsad & Lewis, 2008). Asynchronous instruction is the most common delivery method, although communication may occur through a number of technologies, ultimately resulting in blended, hybrid or fully online courses whose definition depends on the proportion of content delivered online (Parsad & Lewis, 2008).

One form of distance education, self-paced coursework, is based on the concept of independent study, which began in the late 19th century when those who could not attend class in person studied material independently in the form of correspondence courses (Watkins, 1991). For decades, nontraditional students have taken advantage of asynchronous, self-paced courses to complete their studies as institutions employed new technologies including online self-paced course offerings to reach larger audiences (Burton, 2009). A number of institutions are also beginning to provide online competency-based self-paced programs, providing credit for learning often in the form of competency units rather than credit hours (Kelchen, 2015).

Since the 1990s, distance educators have increasingly placed course content online to take advantage of the speed and interactivity available via the Internet, resulting in the phenomenal expansion of distance education noted previously. For example, university course offerings at the distance education office of the University of Missouri's flagship campus are primarily online in semester-based and self-paced formats

(Mizzou Online, 2014); that distance education office, Mizzou Online, was created in 2010 by the integration of the Center for Distance and Independent Study (CDIS) and MU Direct. CDIS closed its few remaining print courses in October 2009, prior to the merger.

This study focuses on the form of distance education known as self-paced coursework. In the United States, a number of organizations, including public land-grant institutions, offer self-paced university, high school, and other courses, including competency-based and massive open online courses (MOOCs). Students work on courses at their own pace and enroll any day of the year. The courses are offered at a distance, either print-based or online; an increasing number of self-paced programs are completely online. While students are given a certain length of time in which to complete their courses, they may complete earlier than their course end date, since they may have earlier academic, financial, or personal deadlines for completion (University of Missouri, 2015).

Campus students often enroll in one or two online self-paced courses each semester to supplement their classroom courses. Nontraditional students generally cannot attend classes on campus and often complete degrees online. In 2004, the College of Arts and Science at the University of Missouri began offering a bachelor of general studies (BGS) degree completion program through self-paced coursework to nontraditional students who could not otherwise complete their degree (CDIS, 2004). Currently, students complete the online BGS degree using a combination of online semester-based and self-paced coursework.

In brief, both campus and nontraditional students enroll in online coursework and may have different characteristics. Consequently, in an attempt to ascertain what

characteristics might promote academic achievement in online courses, this study focuses

on student and institutional or course characteristics for those enrolled in university-level

online self-paced courses. Before addressing the scope of the study, information about

self-paced coursework and other aspects relevant to the study has been provided.

This study examines students enrolled in online self-paced coursework through

Mizzou Online at the University of Missouri's flagship campus. At Mizzou Online,

online self-paced university course completion rates have increased in the past several

years, ranging from 81% to 83% since fiscal 2001-02, to about 90% in 2012 (University

of Missouri, 2013). The institution ranks in the top three of those institutions that report

such self-paced course completion rates (Association for Distance Education and

Independent Learning, 2009). However, annual reports at Mizzou Online also indicate

that course completion rates, or persistence, in online semester-based university courses

are somewhat higher than those for online self-paced courses, as well as grades

(University of Missouri, 2013) so determining what variables affect completion rates and

academic achievement will be useful.

For purposes of this study, persistence is defined as completing an online self-

paced course and academic achievement is defined as the total number of points a student

earns in an online self-paced course, placed on a common scale. Completing an online

self-paced course is equated with persistence due to the self-direction and self-regulation

required. Two time frames are of interest in this study; the length of time each student

took to complete their coursework from their course start date, or enrollment time, and

the length of time each student took to complete their course from the date they submitted

the first assessment, or active completion time, since students have some autonomy in

when they begin coursework due to the self-pacing. Enrollment time will be referenced in the research questions, but both enrollment time and active completion time will be studied.

Statement of the Problem

The literature is lacking in studies of achievement and persistence in online self-paced coursework, which is becoming even more relevant due to massive open online courses (MOOCs), competency-based coursework, and other forms of self-paced course delivery. In recent years, Mizzou Online has also begun offering 16-week self-paced online courses to help students with specific graduation, financial aid, NCAA athletic, or military certification deadlines. Because the 16-week self-paced courses have predetermined start and end dates and checkpoints, comparisons with like 9-month maximum courses that have identical instructors, assessments, and course materials were also of interest. Effective with spring 2016, Mizzou Online reduced the length of the 9-month maximum courses to 6 months maximum. For the spring 2016 term, 37 of the 6-month maximum courses offered included personalized checkpoints based upon the course start date the student chose and the number of assignments the instructor deemed due at each checkpoint.

Significance of the Study

It is clear that distance education is experiencing increased growth due to technological advances and student demand. While comparative studies involving distance education and classroom students have been conducted concerning the impact of delivery method on achievement outcomes (Bowen, Chingos, Lack, & Nygren, 2013; Cavanaugh & Jacquemin, 2015; Means, Toyama, Murphy, Bakia, & Jones, 2009;

Russell, 1999; Shachar & Neumann, 2010; Xu & Jaggars, 2013), little research exists concerning the impact of student and institutional characteristics on achievement in the self-paced format. Regarding student characteristics, Phipps and Merisotis (1999) noted that a significant amount of research in the field of distance education focused on achievement between groups of traditional and nontraditional students and failed to take into account individual differences at the student level. Examples of institutional characteristics that could impact achievement include varying admission requirements and student-adviser ratios at the same institution.

Research that delves into institutional and student characteristics and evaluates achievement may be beneficial to student success. Since many institutions are beginning to offer entire degrees at a distance worldwide, as well as the growth in self-paced massive open online courses and competency-based education, exploring these areas may have international as well as national implications.

Purpose of the Study

The specific purpose of the study is to examine academic achievement and persistence for students enrolled in online self-paced courses. The goal of this study is to investigate how characteristics of students enrolled in online self-paced courses relate to their academic achievement and persistence in those online self-paced courses. Little research exists with a focus on achievement and persistence in self-paced coursework. Both student-level and group-level research is warranted. Achievement in the same self-paced course offered in both the 9-month maximum and 16-week formats will also be studied in a supplemental analysis.

Research Questions

The specific research questions proposed in this study are:

Research Question 1

What is the variability in achievement in online self-paced courses within and between courses; in other words, how much do online self-paced courses vary in their mean achievement?

Research Question 2

On average, are student's age, gender, enrollment time, level in school, persistence, and prior online self-paced course experience related to academic achievement within the online self-paced courses? Enrollment time, or the time it took each student to complete their course from the course start date, and active completion time, or the length of time it took each student to complete the course from the date they submitted the first assessment, are both of interest. Enrollment time will be referenced in the pertinent research questions, but both enrollment time and active completion time will be studied.

Research Question 3

Is the strength of association (i.e., correlational relationships) between student characteristics (age, gender, enrollment time, level in school, persistence, and prior online self-paced course experience) and academic achievement similar across online self-paced courses, or are student characteristics more important predictors of achievement in some online self-paced courses than others?

Research Question 4

How do the online self-paced courses compare in terms of mean academic achievement and in terms of the strength of the student characteristics-achievement relationship, after controlling for course satisfaction?

Research Question 5

What is the variability in persistence in online self-paced courses within and between courses; in other words, how much do online self-paced courses vary in their mean persistence?

Research Question 6

On average, are student's age, gender, enrollment time, level in school, and prior online self-paced course experience related to persistence within online self-paced courses?

Research Question 7

Is the strength of association (i.e., correlational relationships) between student characteristics (age, gender, enrollment time, level in school, and prior online self-paced course experience) and persistence similar across online self-paced courses, or are student characteristics more important predictors of persistence in some online self-paced courses than others?

Research Question 8

How do the courses compare in terms of mean persistence and in terms of the strength of the student characteristics-persistence relationship, after controlling for course satisfaction?

Research Question 9

How does academic achievement compare in the 9-month maximum online self-paced courses and 16-week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

Research Question 10

How does persistence compare in the 9-month maximum online self-paced courses and 16-week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

Assumptions

The following assumption in conducting the study will be made:

1. For the purposes of this study, students enrolled in a combination of online and campus courses will be classified as traditional students and students enrolled solely in online courses will be classified as nontraditional students.

Limitations

The study will be subject to the following limitation:

Other measures such as high school GPA and standardized test scores have been found to influence achievement in distance education courses. However, that information is often unavailable or outdated for nontraditional students and inadequately represents that population, so those measures were not included in this study.

Chapter Two

Literature Review

Literature concerning different aspects of distance education such as its history,

delivery systems, perceptions, student characteristics, and effectiveness will be presented

first in this chapter. A specific form of distance education known as independent study or

self-paced coursework will then be introduced. Finally, information will be provided

concerning a specific lifelong learning provider at the University of Missouri's flagship

campus.

Correspondence Study

In the United States, independent study at a distance, or self-paced coursework,

began in the late 19th century when postsecondary institutions and other organizations

began providing correspondence courses to those who could not attend classes in person;

students included farmers, teachers and businessmen (Watkins, 1991). Students began

earning degrees through correspondence in the 1880s in the U.S. (Schlosser, 1996).

From 1873 to 1897 in Boston, Anna Ticknor offered a personalized

correspondence instruction program primarily to women through the Society to

Encourage Studies at Home that reached a peak of 1,000 students in 1882; Ticknor is

credited with beginning correspondence instruction in the United States (Burton, 2009;

MacKenzie, Christiansen, & Rigby, 1968). Charles Wedemeyer at the University of

Wisconsin, Gayle Childs at the University of Nebraska, William Lighty, and William

Rainey Harper at the University of Chicago were early proponents of distance education,

and their efforts led to asynchronous, formally structured correspondence programs at

public land-grant institutions (Burton, 2009).

In the early 1900s, a secondary education was uncommon. In the United States at that time, 90% of workers did not have a high school diploma (Strom, 1964). Because a better educated populace was needed to work in an increasingly industrialized nation, and workers needed a way to obtain their education without leaving their place of employment or residence, methods such as correspondence instruction were used to provide technical training and general education (MacKenzie, Christiansen, & Rigby, 1968).

In 1882, the Chautauqua school in New York begin offering correspondence courses from October through May as an outgrowth of summer classes held at Lake Chautauqua, offering correspondence courses for nearly twenty years (Noffsinger, 1942). In 1892, William Rainey Harper, the Chautauqua school principal, became the first president of the University of Chicago and organized the new university into five parts, three of which were his own creation including a university extension division that specifically listed correspondence as a teaching method based on Harper's mission to provide services beyond the classroom (Bittner & Mallory, 1933; MacKenzie, Christiansen, & Rigby, 1968). From Chicago, correspondence instruction spread to the extension divisions of several public postsecondary institutions (Noffsinger, 1942).

The University of Wisconsin was the first university to follow the University of Chicago's lead by establishing a correspondence department but differed in that course offerings were primarily vocational (MacKenzie, Christiansen, & Rigby, 1968). In 1915, the National University Extension Association (NUEA) was founded by 22 universities that had created extension divisions (National University Extension Association, 1915;

Pittman, 1998). Bittner and Mallory (1933) estimated that 150,000 correspondence enrollments occurred in 1930, comprised of 73,000 from 34 NUEA universities and colleges, 47,000 from about 70 other universities and colleges, and 30,000 from about 40 teacher training institutions. Bittner and Mallory indicated that 112,500 of those correspondence enrollments were at the university level, 33,000 were non-credit, and 4,500 were at the high school level.

Due to market demand, private commercial entities also began offering correspondence instruction. In the United States, the correspondence format proved especially popular between World Wars I and II. Over two million students enrolled through correspondence each year during the 1920s (Pittman, 2009). Burton (2009) stated that "Millions of individuals…outside the educational mainstream (collectively known as 'non-traditional students') empowered themselves by opting for self-paced, asynchronous, independent study arrangements" (p. 2).

The Carnegie corporation surveyed one-third of the private correspondence schools in 1926 and reported that more students had enrolled in those schools than in all of the resident professional schools, universities, and colleges combined (Noffsinger, 1942). Unfortunately, some of the private correspondence schools were fraudulent degree or diploma mills or guaranteed unrealistic employment opportunities (MacKenzie, Christiansen, & Rigby, 1968). Primarily as a result of a Carnegie study exposing widespread fraud in the commercial schools, the National Home Study Council, now known as the Distance Education Accrediting Association (DEAC), was established in 1926 in an attempt to promote ethical standards in correspondence education (DEAC, 2016; Pittman, 1998). However, Bittner and Mallory (1933) cautioned that the public

generally had difficulty discriminating between good and bad correspondence programs and became lost in the maze of options available, often without realizing how much more costly the private commercial programs were than those offered by public institutions.

New Technologies

To reach new audiences and increase interactivity, correspondence course providers took advantage of new technology. University extension units used radio to deliver correspondence courses from the 1920s through the 1940s, television and film were used as delivery methods or to supplement from the 1950s through the 1960s, and satellite technology and computers were used as delivery mechanisms from the 1970s and beyond (Burton, 2009).

In the 1960s and early 1970s, Charles Wedemeyer provided information about the use of educational satellites and distance programs to those planning the Open University of the United Kingdom (OUUK), which opened in 1971 and improved upon the University of Wisconsin's program by awarding degrees and credits autonomously (Diehl, 2013). Since the early 1990s, providers have increasingly placed courses online to take advantage of the speed, storage capacity, and interactivity available via the Internet, resulting in the phenomenal expansion of distance education noted previously. It is clear that communication technologies and distance education have been historically intertwined (Schlosser, 1996).

Independent Study

In 1955, the NUEA created interest groups or divisions, including the Correspondence Study Division, or CSD (Pittman, 1998). For a number of reasons, including the use of new technologies and an effort to create a separation from the

commercial schools, the term "correspondence study" was replaced by the term "independent study" (Moore, 2003). In the late 1960s, the NUEA changed the name of the CSD to the Independent Study Division (Moore, 2003; Pittman, 1998). The change in terminology to "independent study" was accompanied by a definition still in use today:

> Independent Study consists of various forms of teaching-learning arrangements in which teacher and learner carry out their essential tasks and responsibilities apart from one another, communicating in a variety of ways for the purposes of freeing internal learners from inappropriate class pacings or patterns, of providing external learners with opportunities to continue learning in their own environments, and of developing in all learners the capacity to carry on self-directed learning. Independent study programs offer learners varying degrees of freedom in the self-determination of goals and activities, and in starting, stopping and pacing individualized learning programs, which are carried on to the greatest extent possible at the convenience of the learners. (Wedemeyer, 1971, p. 550)

Distance Education

The earliest reference to the term "distance education" reportedly occurs in a catalog from the University of Wisconsin dated 1892 (LeBaron & Tello, 1998; Verduin & Clark, 1991). At the first National University Extension conference in 1915, William Lighty referred to the teaching methods that William Rainey Harper brought from Chautauqua to the University of Chicago as "distance teaching" ((Lighty, 1915, p. 76). The term distance education has numerous definitions because it comprises such a large field. Moore, Cookson, Donaldson, and Quigley (1990) developed a fairly broad definition of distance education which fits the different formats of distance education in

that it "… consists of all arrangements for providing instruction through print or electronic communications media to persons engaged in planned learning in a place or time different from that of the instructor or instructors" (p. xv).

Verduin and Clark (1991) found three defining elements involved in distance education. First, students and the instructor are separated during a majority of the instruction. Second, some type of educational or technological medium is used to provide course content and communication between students and the instructor. Third, some type of communication has occurred between the instructor or educational institution providing the distance education and the student (Verduin & Clark, 1991).

Distance Students

The distance education audience has historically been adult learners who cannot attend classes in person due to other commitments (Nasseh, 1997). Edelson and Pittman (2001) predicted online education would prove to be popular with all students, including traditional campus students. This prediction has come true as traditional students turn to the online course format (Ginder, 2014) due to course and work scheduling conflicts, campus courses filling before they can enroll, or because they enjoy the media-rich online courses. These factors have increased the popularity of online courses nationwide and the diversity of the audience.

Nationwide, traditional students — those dependents aged 18 to 22 generally living on campus and attending school full time — have become the exception rather than the norm. Most students work, many of them full time, and may have dependents of their own (Pelletier, 2010; Carnevale, Smith, Melton & Price, 2015). The National Center for Education Statistics (NCES) reported that nationwide, at least 74% of all 2011-12

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undergraduate students exhibited one or more of the characteristics generally attributed to nontraditional students. These characteristics ranged from part-time enrollment, full–time employment, financial independence from parents, dependents of their own, waiting to start their postsecondary education, serving as a caregiver, or credentials other than a diploma from a traditional high school (Radford, Cominole & Skomsvold, 2015).

Distance Education Delivery or Formats

Distance education courses may be defined by the way students communicate with the instructor, each other, and the technology used. Synchronous systems require that students and instructors participate simultaneously in the same period of time (Rice, 2006). Examples include the classroom and online courses with components requiring participation at specific dates and times, including semester- or term-based online classes.

Asynchronous courses, on the other hand, are more flexible in that students have the freedom to choose when and where to work on their courses (Edelson & Pittman, 2001). Examples include self-paced or independent study, MOOCs, and competency-based coursework. Hybrid courses may have both asynchronous and synchronous aspects, including required campus visits or classroom meetings.

Distance Education Course Design and Quality Standards

In 1931, the NUEA published and adopted a set of rules, or correspondence study standards, specifically designed to promote and emphasize the equivalence of correspondence courses in content and instruction to courses taught on campus by the same faculty members (Bittner & Mallory, 1933; Pittman, 1998). NUEA changed its name several times over the years, most recently to the University and Professional Continuing Education Association (UPCEA) in 2010 (Pittman, 1998; UPCEA, 2016).

Bittner and Mallory (1933) indicated that efforts made to ensure equivalency often resulted in a heavier workload and higher expectations in the correspondence course than in the same course taken in the classroom along with stricter rules and regulations for correspondence courses, including a limit on how many correspondence courses students could take and have counted toward a degree.

Current guidelines for the effective administration, teaching, and design of quality distance education courses and programs abound, including those written by the Council of Regional Accrediting Commissions (C-RAC) in 2011, UPCEA's Hallmarks of Excellence in Online Leadership published in 2015, and the Quality Matters Higher Education rubrics used to evaluate blended and online courses (Quality Matters, 2014). At each institution, setting standards of quality assurance, surveying stakeholders including campus units to obtain information regarding their needs and perspectives, developing learning analytics to drive improvement in course design and systems of support, and developing a cycle of continuous improvement are assessment tools that may assist with developing an effective, sustainable strategy that ensures student success in online courses and programs (UPCEA, 2015).

Because students generally do not have the opportunity for face-to-face interactions in their online courses, instructors have begun using a variety of techniques to increase engagement, such as gamification, or the use of game elements in course components, and enhanced interaction with materials (Friedman, 2016). The impact of such innovations as gamification has increased student expectations of online course quality; however, instructors should make it clear to students that game-design learning components be taken seriously in order for gamification to be effective (Friedman, 2016)

since gaming may cause students to expect rewards, underestimate the rigor involved in their online course, and assume a fast and easy experience. Friedman (2016) cited Duolingo as an example of a free, gamified interactive language tool designed to help students interact with different languages, as they listen to the proper pronunciation of vocabulary online, view mouse-over translations, and take language quizzes online. Friedman noted that many game-design pieces also provide instant feedback, another helpful student engagement tool.

Competency-based Programs

Competency-based programs have been available in the United States since the 1970s, primarily in continuing or adult education (Klein-Collins, 2013). Outcome or competency-based education (CBE) placed attention on what students should be able to do or know by defining competencies, then, if a course-based model was used, creating curriculum and assessments to assist students with achieving the competencies (Council of Regional Accrediting Commissions [C-RAC], 2015; Klein-Collins, 2012). Students advanced at their own pace to attain proficiency, or mastery, in a competency by demonstrating knowledge, capabilities, and skill as they completed performance assessments, including the application of knowledge in diverse ways. Students might also utilize prior learning, portfolios, work, training programs, and experiential learning as ways to achieve competencies in the course-based model (Council of Regional Accrediting Commissions [C-RAC], 2015; Klein-Collins, 2012).

A subgroup of CBE, direct assessment, only awards credentials, including degrees, on the demonstration of competencies achieved while in the program, excluding prior learning assessment and transfer credit, although hybrid programs may combine

both course-based and direct assessment (C-RAC, 2015). Because competencies are pre-defined and quantifiable, competency-based programs may not measure outcomes using credit hours, since the focus is on verifying learning rather than evaluating seat time or credit hours. However, competency-based direct assessment programs that base their degrees in competency units have developed conversions to credit hours for such purposes as credit transferability, financial aid, or conditions of licensure (C-RAC, 2015; Klein-Collins, 2012).

The escalating cost of higher education in recent years has resulted in renewed interest in CBE, with over 600 postsecondary institutions planning to offer, or currently offering, competency-based programs (Tate & Klein-Collins, 2015). As of spring 2014, 52 institutions reported either offering or starting CBE programs, with nine of those institutions solely offering CBE reporting that they had enrolled nearly 200,000 students (Kelchen, 2015). Eight of those nine institutions reported that over half of the students were enrolled part-time. Part-time completion in CBE programs may actually result in a higher cost to students than traditional programs for those students paying a flat fee for enrollment during a set time period. Many CBE programs do not qualify for federal financial aid, also resulting in higher costs to students using more expensive private loans (Kelchen, 2015).

Massive Open Online Courses

Another form of online course delivery that was designed to reach a larger audience, open online courses, may be taken by many students, with less focus on instructor-student interaction and more focus on students interacting with the materials and with each other, depending on the scalability of the course and the plans for

sustainability. Over 2200 students enrolled in an open online course, Connectivism and Connective Knowledge, at the University of Manitoba in 2008, leading to the new term MOOC, or massive open online course (Fini, 2009). Some MOOCs have the capability of being offered both for credit, for a fee, as well as offered free to students taking the course for no academic credit, often without grades from the instructors or course facilitators, although students may grade work for each other. Students need to have technology skills and often need to demonstrate proficiency in the English language to take a MOOC, although content may be available in multiple languages (Fini, 2009).

As an example of a program that extended asynchronous online coursework including MOOCs to both their distance and traditional students, Berklee Online was founded in 2002 to extend the mission of the Berklee College of Music to students who could not attend campus-based programs, providing high-quality learning experiences to nontraditional students. Their media-rich online courses provided such learning experiences as online keyboard applications for those traveling without music equipment (Cavalier, 2015). Berklee Online expanded free, high-quality learning content by partnering with Coursera and edX to offer MOOCs. In September 2014, the five MOOCs they offered through Coursera surpassed one million enrollments (Cavalier, 2015). Berklee Online launched Bachelor of Professional Studies degrees in fall 2014 at a lower cost to distance students and launched 3 additional majors for a September 2015 start. They also teamed up with Southern New Hampshire University to create a graduate-level music business concentration, preparing students with that concentration in SNHU's online MBA program for leadership positions in the music industry (Cavalier, 2015).

MOOC completion rates may be quite low especially for those enrolling for no

academic credit. However, since those students have reasons for enrolling unrelated to earning academic credit, evaluating persistence for those students may be inappropriate (Fini, 2009). Jordan (2015) analyzed completion and enrollment data for 221 MOOCs offered by 78 institutions from 2011 to 2013. Of the 129 MOOCs with completion data, the median completion rate was 12.6%, with a range of 0.7% to 52.1% (Jordan, 2015).

The number of postsecondary institutions offering or planning to offer massive open online courses, or MOOCs, is fairly small and remained about the same for the 2012-2015 time period (Allen & Seaman, 2016). In 2015, about 11.3% of the academic leaders who completed the College Board's annual survey reported that they offered MOOCs, and about 2.3% planned to offer one (Allen & Seaman, 2016). In 2014, 16.3% of academic leaders at those institutions believed that the MOOC model was sustainable, significantly smaller than the 28.3% who reported this belief when asked about the sustainability of the MOOC model in 2012 (Allen & Seaman, 2016).

While the majority of institutions not currently involved in offering MOOCs no longer plan to offer them in the future, thousands of students currently enrolled in MOOCs nationwide could be impacted by changes in plans to offer MOOCs (Allen & Seaman, 2016). The majority of those enrolling in MOOCs have higher education levels and socioeconomic backgrounds and have other education options than the educationally disadvantaged who were originally predicted to take them, perhaps because those with lower education levels do not have the appropriate technology skills, an unintended usage gap that could influence future decisions to offer MOOCs (Rohs & Ganz, 2015).

Perceptions of Distance Education

At an administrative level, over 63% of the academic leaders completing the

College Board's annual survey of postsecondary institutions in 2015 reported that their long-term strategic plan included online education as a critical component, down from nearly 71% in 2014 (Allen & Seaman, 2016). However, this difference was attributed to a change in response from those who did not offer distance education at their institutions, since 77% of those offering online classes at their institutions reported that online education was a critical component of their strategic plan (Allen & Seaman, 2016). Only 29% of those surveyed indicated a positive acceptance of online education by their faculty, in terms of merit and legitimacy (Allen & Seaman, 2016).

Primarily due to its lack of face-to-face instruction (Sher, 2008), distance education has not always been well received by faculty; Phipps and Merisotis (1999) once called it "a poor and often unwelcome stepchild within the academic community" (p. 7). Moore and Thompson (1990) specifically cited faculty-led requests for ways in which instructor-student and student-student interactions and other effective communication could occur in distance education, as well as how to increase motivation in students.

Rhode (2009) asked students who had completed at least 75% of an educational technology self-paced online course which forms of interaction they preferred and the impact those interactions had on their course experience. Rhode received responses from 10 students who gave interactivity with the course content and their instructor, including informal communications, the highest ratings, identifying those forms of interaction as equally necessary to an optimal experience. Rhode reported that students felt the self-paced format was one of the best features of the course, describing the format as a crucial feature that permitted them the flexibility to participate in the online program. Interaction

between students, including discussion boards, was given the lowest ratings, with students expressing a willingness to do without student-to-student interaction in order to maintain the flexibility of the self-paced delivery format (Rhode, 2009).

Achievement

Student characteristics have been found to affect achievement, persistence, and satisfaction levels of the distance learner. Dille and Mezack (1991) researched the relationship between retention and academic success in telecourses, courses in which material was presented via video in addition to printed study guides and books, and student characteristics by surveying 188 students enrolled in four telecourses at a community college in the southwest. In terms of predicting student success in the telecourse, student characteristics such as locus of control, grade point average, marital status, age, and the number of college credit hours completed were statistically significant ($p = .05$), with success defined as earning a C or better in the course and non-success defined as earning less than a C or withdrawing from the course (Dille & Mezac, 1991).

In one review of distance education literature consisting of 355 research reports, summaries, and papers from 1928-1999 in which researchers reported on achievement outcomes, no significant differences were found in achievement outcomes for those enrolled in distance courses versus those attending class in person (Russell, 1999). Dubin and Taveggia (1968) reviewed 91 comparative studies of college teaching methods that occurred over a 40-year period from 1924 to 1965 and concluded that there were no significant differences in achievement outcomes for those taking a course face to face, whether lecture or discussion, or independent study, whether supervised or self-study. Dubin and Taveggia predicted that while technologies used to teach differed, those

differences would continue to be nonsignificant in terms of student achievement, leading to their belief that the research focus should add a third dimension, the student, to the teaching-learning model, including motivation to learn and other student factors.

Means, Toyama, Murphy, Bakia, and Jones (2009) reviewed 1,132 distance education comparative studies published from 1996 through 2006 and conducted a meta-analysis on studies that included online delivery as one of the methods, quasi-experimental or random assignment designs, and quantitative measures of learning. This process narrowed their focus to 99 studies, 45 of which had enough data to determine 50 effect sizes. Means et al. indicated that on average, students enrolled in online or blended classes with both online and face-to-face elements performed somewhat better than students enrolled solely in face-to-face classes. However, Means et al. noted that a number of learning conditions such as time on task were dissimilar or small sample size in the studies that they reviewed, causing them to express caution in the findings.

Hibbard, Sung, and Wells (2016) compared the achievement outcomes of students enrolled in a self-paced semester-based chemistry flipped course, in which students worked on online content primarily at their own pace and used class meeting times for teamwork or quizzes, to achievement outcomes of students enrolled in the same course in a traditional lecture format. Results indicated that achievement outcomes were better for students who completed the self-paced chemistry flipped course than those who took the traditional chemistry lecture class (Hibbard et al., 2016). Hibbard et al. noted that the self-paced flipped format permitted students to review content, apply knowledge, and practice skills, which promoted subject mastery and knowledge retention, improved attrition rates in the chemistry major, and increased persistence.

Satisfaction

Research in distance education has not focused much on student satisfaction and other affective outcomes (DeBourgh, 1999). DeBourgh (1999) examined course satisfaction for nursing students enrolled in an online graduate program and found that regardless of course delivery method, course satisfaction was primarily related to the effectiveness and quality of the instruction and the instructor. As is the case with many nontraditional students new to distance education, DeBourgh reported that students experienced some anxiety with technology at the beginning of the course but gave high ratings to course technology by the end of the course.

Students enrolled in distance education courses have generally been satisfied with their courses and were characterized as having positive attitudes (Phipps & Merisotis, 1999). Phipps and Merisotis (1999) reviewed several research studies from the 1990s and expressed a concern that many of the conclusions were rendered inconclusive by questionable research methods, noting that a significant amount of the research focused on achievement between groups of traditional and nontraditional students and failed to take into account individual differences.

Of the 1990s research they reviewed, they cited the following shortcomings:

- Extraneous variables were not controlled for, thus the research could not demonstrate cause and effect, since other variables may influence outcomes.

- Non-random subjects. While the best way to control for extraneous variables was random student assignment to the control and experimental

groups, students self-selected enrollment in classroom or distance

education courses. Therefore, variables other than delivery method may

have influenced student satisfaction or academic achievement.

- Questionable instrument reliability and validity. The reliability and

validity of the exams, questionnaires, or attitude scales used were not

included in the published research findings in almost all of the studies

reviewed, and it was likely that the validity and reliability of the

instruments used were not determined (Phipps & Merisotis, 1999).

Sher (2008) adapted or used perceived learning, student satisfaction, student-instructor and student-student interaction scales and surveyed over 200 students enrolled in three online programs at George Washington University in regard to those perceptual areas. Sher indicated that student satisfaction and perceived learning levels reported were primarily moderate to high, with students commenting that the freedom of learning online was greatly worth the trade-off of in-person interaction. Sher did not have access to objective measures of learning such as student grades to strengthen the study but concluded that successful interactions of technology, students, instructors, and content were necessary to maintain satisfaction and learning.

Wang, Shannon, and Ross (2013) sent surveys to more than 2100 students at Auburn University who had taken an online course between 2008 and 2009 that included questions about age, gender, level in school, prior experience with online classes, self-efficacy in terms of online technology, course satisfaction, and self-reported course grades. Wang et al. received 256 completed surveys and analyzed survey responses for relationships between self-efficacy, course outcomes, learning strategies, and

demographic characteristics of students and determined that students with prior online

course experience used learning strategies more effectively and experienced higher levels

of self-efficacy with technology and satisfaction with their online courses and self-

reported course grades. Wang et al. reported that level in school and gender did not

significantly predict self-reported online course achievement outcomes or course

satisfaction. They emphasized the importance of providing introductory online course

orientations and instructor-led student support especially for students enrolled in their

first online course (Wang et al., 2013).

Persistence

Phipps and Merisotis (1999) expressed concern that several studies reported

higher levels of non-completion for students taking distance courses compared to

students in the classroom. Dupin-Bryant (2004) found that students with lower

cumulative grade point averages and fewer years in school were less likely to complete

an online semester-based university course. Dupin-Bryant suggested that online

orientations might benefit students, since students with previous computer experience and

university coursework were more likely to complete their online courses.

Stone, Tudor, Grover and Orig (2001) conducted a study that surveyed 52 higher

education institutions regarding their distance education programs. They conducted 15-

to-30 minute telephone interviews with administrators of the distance education units at

those institutions and asked 11 questions about distance program longevity, program

completion rates or persistence, admission requirements, grade point averages,

enrollment levels, and the compatibility of majors within academic units to the distance

format. Stone et al. used grade point averages to compare distance and traditional campus

programs and concluded that GPA differences illustrated the incompatibility of certain majors with the distance delivery method.

Stone, Tudor, Grover and Orig (2001) reported that grade point averages for the distance learning programs were better at institutions with admission requirements for those programs, such as requiring a certain number of courses before acceptance to a distance program. No significant enrollment growth was attributed to distance education. Stone et al. suggested that new growth in distance programs might occur with traditional students, rather than nontraditional students.

However, the method of data collection was unclear as they did not indicate what grade point averages and program completion rate totals — by major within academic unit or division, by distance learning programs compared with classroom programs overall at each institution, or by some other aggregate — were self-reported in the telephone interviews (Stone, Tudor, Grover and Orig, 2001). The best unit-of-analysis measure for grade point averages and course completion or persistence would have been at the individual student level. It was also not clear if the distance education administrators had access to the data requested for campus students, so such self-reported data might not be entirely accurate.

Stone et al. (2001) appeared to consider majors offered by academic units as separate entities, if offered on campus or at a distance to nontraditional students. Since students may be completing courses both at a distance and on campus, disaggregating grade point averages and completion rates for those academic units and majors may not be possible. Regardless, data was not collected at the student level, and their study did not take into account individual differences (Stone et al., 2001).

In their published research, Stone et al. (2001) did not include any of the data collected nor sample survey items. It was not clear if Stone et al. checked data for linearity, outliers, truncated range, or if the reported values were scaled the same. The assumptions made in this research study were also a concern; Stone et al. indicated that they were comparing nontraditional students enrolled at a distance to traditional students enrolled in a classroom, but it is possible that those enrolling in the distance courses were also traditional students. In fact, Stone et al. noted that their findings suggested that those enrolled at a distance may be "former" traditional students.

The literature shows that high distance education dropout rates, or low completion rates, are a concern; the self-directed aspects and autonomy inherent in distance education may lead to procrastination and lower achievement or completion rates (Rice, 2006). While self-directed learning provides autonomy, such freedom may also result in non-completion and academic self-handicapping. Academic self-handicapping "refers to strategies, such as procrastinating and fooling around, that are used by students so that if subsequent performance is low, these circumstances, rather than lack of ability, will be seen as the cause" (Midgley et al., 1997, p. 10). New technologies such as gamification, designed to increase student engagement, may cause students to underestimate the work involved in an online course especially if they do not take the game-design learning experiences seriously (Friedman, 2016).

Some of the factors that may affect the persistence of online learners are described below:

In the specialized learning environment of web-based instruction, the ability to work independently, sustain one's focus on personal and academic goals, maintain

motivation in spite of conflicting commitments, and demonstrate computer proficiency are among some of the qualities and life approaches that increase successful completion. (Holder, 2007, p. 246)

In addition to academic preparedness, Holder (2007) listed such attributes as computer self-efficacy, self-direction and self-discipline, time management, and student engagement as predictors of persistence. Holder administered a 60-item survey that focused on such areas as academics, environment, and hope to 407 students enrolled in online degree completion programs at Indiana Wesleyan University and reported that students who persisted tended to have higher scores in self-efficacy, time management, and emotional support. For the academic scales on the whole, Holder did not find significant differences as a result of those factors for those who persisted and those who did not; he also reported an unexpected finding in that students with higher levels of self-direction or autonomy were less likely to persist in their online degree programs and concluded that the cohort-based lockstep structure of the online programs at the institution may have resulted in frustration on the part of students with higher levels of autonomy and ultimately their decision to leave the online program.

Age and Gender

Whether student age and gender have a potential bearing on persistence and achievement outcomes in online courses has been researched in several studies, and results have been mixed (Aragon & Johnson, 2008; Cochran, Campbell, Baker, & Leeds, 2014; Dille & Mezac, 1991; Gerlich, Mills, & Sollosy, 2009; Willging & Johnson, 2009; Wojciechowski & Palmer, 2005). Aragon and Johnson (2008) cited statistics from community colleges reporting non-completion rates in online courses up to 20% higher

than classroom non-completion rates. Aragon and Johnson reviewed data for 305 students who enrolled in online courses through a community college and found no significant differences in age, ethnicity, or financial aid eligibility for those who persisted to complete their courses and those who did not. The percentage of females and those with higher GPAs who completed a course were significantly higher than the percentage of males and those with lower GPAs who completed (Aragon & Johnson, 2008).

Achievement in a self-paced semester-based online management course was evaluated in terms of the effects of locus of control, cumulative GPA, age, and gender (Gerlich, Mills, & Sollosy, 2009). While Gerlich et al. (2009) reported that only cumulative GPA was found to significantly predict achievement on the three learning outcomes they chose — two assessment scores and total course points — age was negatively correlated with performance on the three outcomes. Age and gender were not found to be significant predictors in their study; sample size was not provided in the study (Gerlich et al., 2009).

Willging and Johnson (2009) analyzed demographic data such as gender, age, ethnicity, geographic location, cumulative GPA, and occupation for 28 students who dropped out of a graduate online master's degree program in order to determine if those variables predicted persistence and reported that those variables did not predict persistence. In a follow-up interview with 10 of the students, Willging and Johnson determined that the students dropped out of the online program for a variety of reasons including working full-time or enrollment in too many online graduate courses. Willging and Johnson concluded that persistence was a multifaceted outcome that may be unique to each student or online program.

Level in School

Cochran, Campbell, Baker, and Leeds (2014) analyzed a large sample of over 2,300 undergraduate students enrolled in an online class during spring 2010 to evaluate whether student characteristics such as age, level in school, financial aid, ethnicity, gender, cumulative GPA, and previous online course withdrawals were related to their likelihood to withdraw from their current online courses; over 60% of the students were seniors. Cochran et al. determined that level in school, cumulative GPA, and prior online course withdrawal history significantly impacted the students' current online course withdrawal propensity. Cochran et al. also found that students with a higher cumulative GPA were less likely to withdraw from their current online courses, and students at lower levels of school (class standing) or those with prior online course withdrawal history were more likely to withdraw.

For the spring 2010 online courses they studied, Cochran, Campbell, Baker, and Leeds (2014) reported 30.3%, 25.3%, 20.5%, and 12.6% withdrawal rates for freshmen, sophomores, juniors, and seniors, respectively, for an average withdrawal rate of 16.8%. Older students with merit-based scholarships or no loans were not as likely to withdraw (Cochran et al., 2014). Cochran et al. suggested that increased monitoring and support be provided to students with lower cumulative GPAs, freshmen, and sophomores, and that future withdrawals could potentially be alleviated by providing some type of follow up when students withdrew from their first online course.

Chen, Lambert, and Guidry (2010) used hierarchical linear modeling (HLM) to study whether institutional characteristics such as public or private school, the Carnegie

classification (highest degree awarded by the school), and the institution's geographic

location such as city or rural as well as student characteristics — gender, enrollment

status, ethnicity, and level in school — played a part in the likelihood of the student

enrolling in an online class. They classified course delivery methods as online, hybrid,

and face-to-face, resulting in seven possible combinations of those enrollment methods,

and asked students at 45 postsecondary institutions to self-report their current academic

year enrollment patterns (Chen, Lambert & Guidry, 2010). The likelihood of a freshman

taking an online class was slightly higher if the school was private versus public, and

slightly lower if the highest degree awarded was at the baccalaureate level compared to

institutions granting doctoral degrees.

Their research results indicated that freshman and senior minority or part time

students were more likely to take online classes, freshman business majors were slightly

more likely to enroll online, and seniors majoring in professional fields such as nursing,

education, or occupational therapy were more likely to enroll in online classes (Chen,

Lambert & Guidry, 2010). Based on their findings, Chen et al. (2010) stressed the

importance of providing quality online courses to these audiences of increasingly

nontraditional, part-time, minority, and working students to avoid any unintended

marginalization or educational segregation.

Prior Online Course Experience

In a study of 124 adult students between the ages of 30 and 45 enrolled in

undergraduate independent study courses for the first time, Kemp (2002) investigated

relationships between persistence, external commitments, resiliency, and life events and

found a significant difference between groups of completers and non-completers for work

commitments, suggesting that external work commitments were strong predictors of persistence. While other research indicates that previous experience with distance courses may increase course completion rates (Aragon & Johnson, 2008), Kemp found no significant difference between groups of completers and non-completers for students with prior experience with distance courses. Kemp also found no significant differences for life events or females and males between the groups who persisted and those who did not.

Using three years of completion data for an undergraduate online course in business in which the instructor and textbook were identical, Wojciechowski and Palmer (2005) analyzed such student characteristics as prior online course experience, gender, age, GPA, class orientation attendance, time to complete (8- or 16-week sessions), writing, reading, English and other standardized test scores, full or part-time student status, and prior course withdrawals to determine if there was a relationship with student success, defined as earning a C or better letter grade in the course. For the 179 students studied, results indicated a significant relationship between course grade and prior online course experience, GPA, class orientation attendance, reading and English standardized scores, age, and prior course withdrawals. For those students who achieved a C or better letter grade, results indicated a significant relationship between course grade and GPA, class orientation attendance, age, prior course withdrawals, and time to complete in terms of the 8- or 16-week session (Wojciechowski & Palmer, 2005).

For the data they analyzed, Wojciechowski and Palmer (2005) indicated that GPA and class orientation attendance were the predictors that most influenced student success and that students who withdrew from fewer courses or had more prior online course experience earned better grades in the course. They also found a positive relationship

between age and course grades, as older students performed better in the course. Wojciechowski and Palmer did not find any significant relationships with grades for gender or full- or part-time student status but did report that successful students performed better in the 16-week format than the 8-week format.

Lint (2013) analyzed student characteristics to identify relationships in regard to persistence for 169 students who had enrolled in an online course at a community college in Maryland and found that external demands on time or external attribution including social media had a significant negative influence on student persistence, identified for purposes of her study as enrolling again at the same institution the next term, transferring to another institution, or graduating. Lint surveyed students in regard to academic integration, or contacts with the institution; external attribution, or external demands on time for work, friends, family, and social media; social integration or the extent that they received moral support from family, friends, and employers for their educational goals; and whether they failed the course, which she defined as academic incompatibility. Lint found that prior online experience, academic integration, and academic incompatibility also had a significant relationship with persistence. Lint also reported that marital status and GPA were significantly correlated with persistence.

Helms (2014) analyzed student characteristics for students who enrolled in his psychology online semester-based and in-person campus sections the same semester at Kennesaw State University. Students self-selected the online or in-person course, and both sections included the same course materials, grading rubrics and grading scale, assignments, due dates, and discussion board opportunities. Helms indicated that students also used the same learning management system to submit online assignments and take

exams. Students in those course sections were all psychology majors, but the groups differed significantly on some factors prior to enrolling in the course; for example, students enrolled in the online course had significantly higher prior online course experience and significantly lower cumulative GPAs than those who enrolled in the face-to-face course section (Helms, 2014).

Despite the difference in prior online course experience, Helms (2014) found that as students progressed in the course, there was a significant difference in the number of missing assignments, with 65% of students enrolled in the online section missing one or more assignments, compared to 19% of those in the campus section. As with cumulative GPA, and partly as a result of the missing assignments, course grades were also significantly lower for students enrolled in the online course. Helms speculated that other competing life events such as work and family demands may have impacted students choosing to enroll in online courses at his institution; while the students enrolled in his online course had more prior online course experience, it is possible that those competing demands also played a part in their lower cumulative GPAs and course grades. Helms suggested that while the online modality gave students with multiple demands on their time an enrollment option, those students may have been less concerned with good grades as an outcome or had lower expectations of themselves in grade achievement.

Self-paced Format

While self-paced courses generally still include features such as lessons or modules, objectives, assignments, and proctored exams as in the old correspondence model, online self-paced courses also likely include such features as videos, digital graphics and images, announcement pages, online tutorials, practice quizzes or helpful

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materials, and links to readings in electronic journals, with the instructor or course developer serving as a facilitator of learning (Fish & Wickersham, 2009). Online self-paced courses are generally asynchronous, in that students may complete a course at their pace, such as from 6 weeks to 9 months, and may enroll any time of the year (Edelson & Pittman, 2001). This format generally does not include interaction between students accordingly as each student is usually at a different point in the course with the instructor.

Students enroll in self-paced courses for various reasons, using them to supplement their on-campus curriculum, reduce scheduling conflicts, or earn credit toward a high school diploma or degree, often while out of school or working (CDIS, 2000). Students who enroll in university courses also do so to take courses that are full on campus, to meet course prerequisites, restore academic eligibility, or to meet requirements for certification or job advancement (CDIS, 2000). Students may choose to enroll in the same course at the same time to work on the course together.

Self-paced proponents cite several advantages that affect both students and institutions. One oft-cited advantage is that students can complete online courses at home; generally, the only travel and transportation costs involved are associated with the taking of proctored exams (CDIS, 2000). Another advantage is that the institutions which provide the courses do not need to provide classroom space for distance learners other than exam testing centers, thus decreasing the cost of physical facilities, parking, and maintenance (Khan, 1997). A third advantage of online courses is that many if not all features are asynchronous, without required meetings, discussions, or chats at set times (CDIS, 2000); since students may complete courses in less time at their own pace such as in 6 weeks, this feature is appealing and marketable (Edelson & Pittman, 2001). On a

related note, innovation in technology and self-paced course design have facilitated student engagement in such ways as interactive exercises with personalized feedback in math courses and listening exercises and practice with pronunciation in language courses with opportunities to apply learning, as with the Duolingo interactive game-design pieces (Friedman, 2016).

Self-paced courses also have their critics who cite some shortcomings. One disadvantage concerns withdrawal rates that are generally higher than those for campus-based or online semester-based course instruction (Siegenthaler et al., 2014). Finishing a self-paced course may be more difficult for a student who is not self-directed or self-disciplined (Phipps & Merisotis, 1999); prior experience with a self-paced course should not be underestimated. Students may not feel connected to the class or the educational institution (Rice, 2006) since there may not be much interaction with the instructor or other students. However, including interactive exercises, game-design pieces, and the ability to interact with the instructor in different ways reduces this concern (Friedman, 2016); for example, at the University of Missouri, such student support services as 24-hour online tutorial services, orientation courses, face-to-face or Skype orientations, self-paced courses with instructor-monitored checkpoints, and the potential for meetings with instructors – whether online, in person, or by phone – have been implemented to keep students on track (Mizzou Online, 2015).

In an experiment designed to measure the effect of student support in online math education courses on student outcomes in a professional development course offered through the Education Development Center in Massachusetts, four sections were created, ranging from an online semester-based section with a high level of student support

including a math instructor, interaction among students as they worked on course content

together, and an online facilitator, to a self-paced section with none of those features, and

two additional online semester-based sections that included some support (Russell,

Kleiman, Carey & Douglas, 2009). Russell, Kleiman, Carey, and Douglas (2009) found

that the students — middle school math teachers — rated the course highly, including

satisfaction scores on course evaluations, with positive changes occurring in several pre-

and post-test scores and measures, and no significant difference in intended outcomes

among the four sections. Russell et al. suggested that in terms of math education for

teachers, quality courses with rich materials and learning activities may sufficiently

provide positive results making high levels of peer and facilitator interaction unnecessary.

A research team at Clayton State University created an online self-paced course in

American government with a number of engaging online interactivities in order to

compare achievement in the self-paced section with the course offered in online

semester-based and campus formats; the same instructor taught all three sections using

the same content, exams, and course materials (Southard, Meddaugh & France-Harris,

2015). They reported that students in the self-paced course did as well on the exams as

students in the classroom section and better than students enrolled in the online semester-

based section. However, students were required to have a GPA of 3.0 or better to enroll

in the self-paced version; Southard, Meddaugh, and France-Harris (2015) did not indicate

that the other sections had a similar prerequisite, which may have influenced the results.

While Southard et al. were correct in indicating there is a paucity of research for the self-

paced format, they seemed unaware that the self-paced format has existed for many

years, calling it a new delivery method.

In an effort to examine student and institutional characteristics for a distance program more thoroughly, this study will focus on achievement for students enrolled in online self-paced courses through Mizzou Online at the University of Missouri, described in the next section.

Mizzou Online

As part of the University of Missouri's land-grant mission to extend education throughout the state, the Center for Distance and Independent Study (CDIS) was established as a unit of its Extension division in 1911 (CDIS, 2000). High school courses were initially offered through the mail so that teachers could meet new state certification requirements requiring them to complete one or more years of high school; the cost of such courses was $7.50 per half unit (University of Missouri Extension, 1913). University courses were initially offered through the mail only to individuals 21 years of age or older at a cost of about $3.50 per semester credit hour (University of Missouri Extension, 1912).

In the late 1990s, CDIS began converting print-based university and high school print-based courses to online courses and completed the process in 2009 (C. Newton, personal communication, April 4, 2016). In addition to offering individual courses, in the fall of 1999 CDIS officially opened MU High School (CDIS, 2000), which also provided a high school diploma program for students needing that option. In 2004, the College of Arts and Science began offering a bachelor of general studies (BGS) degree completion program through independent study to nontraditional students who could not otherwise complete their degree (CDIS, 2004). Currently, students complete the online BGS degree with online semester-based and online self-paced coursework and the program recently began accepting students at the freshman level as Arts and Science online semester-based

course options have expanded. With the assistance of their adviser, the students create and work through a flexible online graduation plan that they can view each time they log into the self-paced learning management system. Based on those graduation plans, over one hundred students are actively enrolled in the online BGS degree program at any one time, and two hundred students have graduated from the BGS online degree program since 2004 (E. Oncken, personal communication, December 11, 2015).

In 2010, CDIS and MU Direct, which offered online semester-based courses and programs, merged to form Mizzou Online, and MU High School became part of the College of Education; over 1,000 courses and about 90 degrees and certificate programs are offered by university academic units through Mizzou Online (University of Missouri, 2015).

Major components that are included in most of the online self-paced courses offered through Mizzou Online are the following:

- Home Page—provides the instructor's name and contact information, contact information for Mizzou Online, any special notes from the instructor, and links to online tutorial or other services

- Guidelines—provides the University of Missouri's (MU's) regulations

- Overview—outlines the specifics and describes the purpose of the course, including a list of course materials required and study suggestions

- Lessons—the primary instructional unit of the self-paced course; most contain a purpose, objectives, a reading assignment and/or other activities, discussion, and study questions

- Progress evaluations—open-book assignments that test the student's

knowledge and understanding of the material discussed

- Grades and assessments page—provides the grading scale and information about the graded assessments for the course including exam details (CDIS, 2000).

Online self-paced courses at the University of Missouri (MU) are developed by a faculty member or graduate student chosen by the chair of the department that offers the course; as of 2016, about 160 online self-paced courses were offered by MU's academic units through Mizzou Online, primarily at the undergraduate level (Mizzou Online, 2016). The unprecedented growth across the nation in online enrollment is reflected at MU, as 15,438 MU students, or 39% of the total MU student population, took one or more online semester-based and self-paced courses in academic year (AY) 2014-15, a student growth rate of 106% over the past five years, which resulted in 30,738 online enrollments in AY 14-15, an enrollment growth rate of 101% over the past five years (University of Missouri, 2015).

Increases in enrollment have been due to increases in campus student enrollment as well as the elimination of restrictions on self-paced and online enrollment for campus students. Until 2002, enrollment in self-paced correspondence courses at MU were flagged with an *'–e'* for extension on transcripts, and campus students were generally permitted to take only a few self-paced correspondence courses through CDIS with their dean's approval (Smith & Nagel, 2010). Until 2002, self-paced correspondence course grades were generally stored on cards in a vault in the registrar's office rather than the electronic records system, and withdrawals were not reported (Smith & Nagel, 2010). Until 2003, the few video courses offered through CDIS were the only courses that could

be counted in the last 30 hours of MU residency requirement (Smith & Nagel, 2010).

In 2002, the academic policies governing self-paced courses changed, as the *'-e'* was removed from transcripts, enrollments were reported at the time of enrollment, and course grades including withdrawals were reported and housed in the registrar's electronic records system; reporting enrollments at the time that they occurred permitted such student services as library access and financial aid (Smith & Nagel, 2010). The residency requirement was also amended in 2003 to state that 30 of the last 36 hours would need to be completed with MU coursework, which included self-paced courses (Smith & Nagel, 2010). While enrollment in self-paced courses at MU increased somewhat as a result of these academic policy changes, large enrollments have occurred primarily since 2012, when students began using the registrar's student services system, myZou, to enroll in online self-paced courses.

This growth has also created some student support challenges. For example, in AY 2014-15, Mizzou Online staff physically proctored 16,264 exams and sent 5,218 exams to proctors worldwide (University of Missouri, 2015). Most of the exams proctored in-house were taken in an exam space at Mizzou Online that holds about 25 students per exam session.

Since AY 2011-12, other than a slight decrease to 2,978 students in AY 2012-13, at least 3,000 students annually have been classified as distance students, admitted to a distance degree program at MU or admitted as non-degree or post-baccalaureate to take online courses at MU as shown in Table 1. Three times as many graduate distance students as undergraduate distance students enroll each year since the number of graduate degrees or certificates offered at a distance far outweigh the number of undergraduate

degrees offered at a distance. For example, in AY 2014-15 when MU offered 80 graduate

degrees and certificates and 9 undergraduate degrees at a distance, 867 undergraduate

distance students and 2564 graduate distance students, for a total of 3,431 distance

students, enrolled through Mizzou Online (University of Missouri, 2015).

About 10% of the student body at MU are classified as distance students. For

example, in AY 2014-15, 3431 students were classified as distance out of 35,441 total

students based on the university's fall 2014 headcount, or 9.7 percent (University of

Missouri Enrollment Management, 2014; University of Missouri, 2015). In AY 2014-15,

the average age of distance students enrolled at the University of Missouri through

Mizzou Online was 29 at the undergraduate level and 36 at the graduate level (University

of Missouri, 2015).

Table 1

Number of Distance Students at MU, AY 2011-15

Academic Year	Undergraduate	Graduate	Total
2011-12	725	2396	3121
2012-13	712	2266	2978
2013-14	807	2420	3227
2014-15	867	2564	3431

Note: Adapted from University of Missouri Distance Education Reports, AY 2011-12, 2012-13,
AY 2013-14, and AY 2014-2015.

Since 2010, the number of students taking at least one course offered through

Mizzou Online has increased 106%, from 7,480 students in AY 2010-11 to 15,438

students in AY 2014-15, with most of the growth occurring at the undergraduate level, as

shown in Table 2 (University of Missouri, 2015). The majority of undergraduate students

enrolling in courses offered through Mizzou Online are designated as campus students. In AY 2014-15, 11,283 undergraduate campus students, or 73.1% of the students who took courses offered through Mizzou Online, enrolled for such reasons as class scheduling conflicts (University of Missouri, 2015). In AY 2014-15, the average age of students enrolled in at least one online course through Mizzou Online was 24 (University of Missouri, 2015).

Table 2

Number of Students Enrolled in at Least One Class through Mizzou Online, AY 2011-15

Academic Year	Undergraduate	Graduate	Total
2010-11	4503	2977	7480
2011-12	6141	3014	9155
2012-13	9632	2980	12612
2013-14	11009	3106	14115
2014-15	12150	3288	15438

Note: Adapted from University of Missouri Distance Education Report, AY 2014-2015.

Online Achievement Studies at MU and Student Characteristics

Demographics for the student population at MU differ from the national trend depicting increasing nontraditional student populations (Carnevale et al., 2015) as the majority of students at MU are traditional students enrolled on campus in face-to-face courses (University of Missouri Enrollment Management, 2015). For fall 2015, MU reported that 81.9% of students were age 18 to 24 including students in graduate studies and the professional fields, and 93.6% of MU students were enrolled full time in 12 or more hours each semester (University of Missouri Enrollment Management, 2015). About 6,500 students, or 18.3% of the total number of 35,448 students enrolled in fall

2015, lived in residential housing on campus (University of Missouri Residential Life, 2015).

Regarding employment, 39% of 1,014 students who responded to a 2012 survey conducted by the MU Office of Student Affairs reported that they did not work during the academic year, and the majority of those employed worked 15 hours or less per week (A. A. Grabau, personal communication, December 21, 2015). In 2014, about 500 MU students answered a Student Affairs survey about out-of-class activities; an average of 68% of those students reported that they did not work (ETC Institute, 2014).

MU students employed on campus who responded to the 2014 survey indicated that they generally worked 8-11 hours each week, and students who worked off-campus reported that they worked 12 or more hours each week (ETC Institute, 2014). It was unclear whether distance students were asked to participate in either the 2012 or 2014 survey or whether they responded to the survey questions if they received the surveys (A. A. Grabau, personal communication, December 21, 2015).

A few studies comparing achievement in online versus face-to-face courses have been conducted at the University of Missouri. Summers, Waigandt, and Whittaker (2005) reported no statistically significant differences in grades for an MU statistics course taken by nursing students when comparing grades for those who took the course in person versus online. However, students enrolled in the online course were significantly less satisfied with the course, instructor, and assessments than those who took the course in person, even though those aspects were the same in both modalities (Summers, Waigandt, & Whittaker, 2005).

In 2014, results of a research study comparing online, classroom, and self-paced

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course delivery that had implications for this study were shared at a teaching renewal conference; specifically, three courses offered online in both semester-based and self-paced formats with 730 enrollments were compared and grades found significantly higher in the semester-based online format (Siegenthaler et al., 2014). However, for that study, the research team did not assess the courses in terms of having the same grading scale, assessments, proctored exams, or course materials (Siegenthaler et al., 2014). Also, using class size as a covariate as in the 2014 study would not have much relevance for self-paced courses since students were at very different points in their self-paced coursework over two or three semesters leading to uncertainty about actual instructor load and volume of submitted coursework (Siegenthaler et al., 2014).

Summary

It is clear that distance education is experiencing increased growth due to technological advances and student demand. While numerous studies have been conducted concerning achievement outcomes for distance students compared to on-campus students (Bowen, Chingos, Lack, & Nygren, 2013; Cavanaugh & Jacquemin, 2015; Means, Toyama, Murphy, Bakia, & Jones, 2009; Russell, 1999; Shachar & Neumann, 2010; Xu & Jaggars, 2013), little research exists concerning institutional and student characteristics for those enrolled in self-paced coursework. Many institutions are beginning to offer entire self-paced degrees online as well as self-paced competency-based programs and massive open online courses that enroll thousands of students worldwide; therefore, the implications of examining the online self-paced trend extends worldwide. The next chapter describes the specific study proposed.

Chapter Three

Method

Sample and Participant Selection

The target population consisted of a year of university online self-paced course completions and non-completions through Mizzou Online. Data for about 12,000 enrollments from AY 2014-15 were included. Enrollments in the internship progress assessment system were not included as they primarily assessed internship status. Enrollments with pass/fail (S/U) grading scales and no points recorded were not included since total scores could not be calculated for them.

Some students enrolled in more than one self-paced course for that academic year, for a total of 8,759 students enrolled, consisting of 4015 males and 4744 females, ranging in age from 16 to 73 with a mean age of 21.88 ($SD = 4.406$). By academic level, those students accounted for 1238 freshmen, or 14.1%, 1789 sophomores, or 20.3%, 2130 juniors, or 24.3%, 3327 seniors, or 38%, and 275 graduate students, or 3.1%. The majority of enrolled students were seniors.

Procedures

Data Collection

University online self-paced non-internship course completions and non-completions at Mizzou Online for the 2014-15 academic year served as the source of potential cases. Information was collected from Mizzou Online's independent learning management system, ILMS, including demographic data such as gender and academic level.

Non-completers were defined as those students who did not finish the course and either withdrew from the course or received a failing grade from the instructor after the course end date; students who withdrew could receive a failing grade instead, based on whether they were passing at the time they withdrew. Completers were defined as those students who finished their graded assessments, specifically homework assignments and exams, and received a course grade. SPSS and SAS were used to create the persistence variable (0 = non-completer, 1 = completer) and other variables as needed for this study.

Alphanumeric fields were changed to numeric with appropriate labels for academic level (10 = Freshman, 20 = sophomore, 30 = junior, 40 = senior, GR = 50 = graduate), and course delivery mode (-1 = 8 week, 0 = 16 week, 1 = 9 month). Orthogonal coding was used for course delivery mode since planned comparisons were intended. Values were also calculated for age at the time of enrollment, enrollment time, and active completion time. Age (rounded to the nearest year) was calculated as the age of the student at the beginning of the semester in which they enrolled.

A concatenated course title/instructor variable was created, then de-identified, for a total of 166 unique course title/instructor combinations. Course evaluation data consisting of 22 items was also used. The self-paced course evaluation items covered areas such as satisfaction with the course content, assessments, and the instructor. A variable denoting overall course satisfaction was calculated for each course using factor analysis for use at level two in the HLM analysis.

Research Questions

The specific research questions proposed in this study were:

Research Question 1

What is the variability in achievement in online self-paced courses within and between courses; in other words, how much do online self-paced courses vary in their mean achievement?

Research Question 2

On average, are student's age, gender, enrollment time, level in school, persistence, and prior online self-paced course experience related to academic achievement within online self-paced courses? Enrollment time, or the time it took each student to complete their course from the course start date, and active completion time, or the length of time it took each student to complete the course from the date they submitted the first assessment, were both of interest. Enrollment time was referenced in the pertinent research questions, but both enrollment time and active completion time were studied.

Research Question 3

Is the strength of association (i.e., correlational relationships) between student characteristics (age, gender, enrollment time, level in school, persistence, and prior online self-paced course experience) and academic achievement similar across courses, or are student characteristics more important predictors of achievement in some courses than others?

Research Question 4

How do the online self-paced courses compare in terms of mean academic achievement and in terms of the strength of the student characteristics-achievement

relationship, after controlling for course satisfaction? Does course satisfaction significantly predict achievement?

Research Question 5

What is the variability in persistence in online self-paced courses within and between courses; in other words, how much do online self-paced courses vary in their mean persistence?

Research Question 6

On average, are student's age, gender, enrollment time, level in school, and prior self-paced course experience related to persistence within online self-paced courses?

Research Question 7

Is the strength of association (i.e., correlational relationships) between student characteristics (age, gender, enrollment time, level in school, and prior online self-paced course experience) and persistence similar across courses, or are student characteristics more important predictors of persistence in some courses than others?

Research Question 8

How do the online self-paced courses compare in terms of persistence and in terms of the strength of the student characteristics-persistence relationship, after controlling for course satisfaction? Does course satisfaction significantly predict persistence?

Supplemental analyses focused on a comparison of online self-paced courses that had identical assessments, instructors, and materials, as indicated below.

Research Question 9

How does academic achievement compare in the 9-month maximum online self-paced courses and 16-week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

Research Question 10

How does persistence compare in the 9-month maximum online self-paced courses and 16-week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

Statistical Analyses

Design

Students chose the type of courses in which they enrolled at MU; because random assignment did not occur, and students self-selected the course and delivery method, this research design was observational (Cochran, 1983). Hierarchical linear modeling (HLM), also referred to as multilevel modeling (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013), was used to answer the research questions for the nested design of students within courses. HLM is useful when data is organized in hierarchies, or levels, such as students within classes within schools (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013). Underlying the hierarchical linear modeling was the assumption that institutional or course characteristics such as the type of courses offered at the institution, characteristics of the student body, persistence or completion rates, and the overall satisfaction of students with self-paced courses offered at the institution have a differential impact on student achievement.

Hierarchical Linear Models

Historically, statistical techniques like regression have inadequately addressed hierarchical structures, as illustrated by problems of unit of analysis, aggregation bias, and precision misestimates (Raudenbush & Bryk, 2002). In nested designs, there may be interactions at the lower and higher levels, such as the effect of instructor enthusiasm on student motivation (Tabachnick & Fidell, 2013). HLM enables modeling of cross-level and within-level interactions for predictors and variance partitioning among levels (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013).

As an extension of traditional linear models, hierarchical linear models are still based on basic assumptions of normality and linearity but result in models that are statistically correct without wasting information (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013). If students are nested within schools and traditional regression techniques are used, student variation may be lost if the school is chosen as the unit of analysis, and if students are chosen as the unit of analysis during conventional regression, independence of observations and bias may be problematic since students at the same school often share commonalities affecting achievement (Raudenbush & Bryk, 2002; Braun, Jenkins, & Grigg, 2006). HLM solves this issue by taking nested structures into account and permitting variable and variance incorporation at all levels (Raudenbush & Bryk, 2002; Braun, Jenkins, & Grigg, 2006).

Metric choices for level-1 predictors often include grand-mean or group-mean centering to provide meaning to intercept parameters (Raudenbush & Bryk, 2002). The dichotomous variables used in this study, gender ($0 = $ male, $1 = $ female), persistence, prior self-paced experience, and academic level ($0 = $ lower division, $1 = $ upper division)

remained uncentered so that their coefficients in HLM could be interpreted as group

mean differences (Wang, Osterlind & Bergin, 2012). Exploratory model building is

useful where models with level-1 predictors are analyzed, including cross-level

interactions, and predictors dropped unless they enhance prediction information

(Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013; Wang, Osterlind & Bergin,

2012). This type of model building and trimming was proposed for use in this study.

Bernouilli Models

Because a dichotomous variable such as persistence only has two possible

outcomes, 0 and 1, the assumptions of normality and linearity cannot be met in its use as

a dependent variable. The standard HLM level-1 model would not be appropriate since

the level-1 random effect is not normally distributed (Raudenbush & Bryk, 2002). For

binary outcomes, a Bernouilli, or binary, sampling model and logit link may be used. For

m_{ij} trials where Y_{ij} is defined as the number of successes and φ_{ij} is the probability of

success on each trial,

$$Y_{ij} \mid \varphi_{ij} \sim B\left(m_{ij}, \varphi_{ij}\right)$$

where Y_{ij} has a binomial distribution with the probability of success per trial as

φ_{ij} with m_{ij} trials (Raudenbush & Bryk, 2002). The Bernouilli distribution is a special

case where the binary Y_{ij} has a value of unity or zero when $m_{ij} = 1$. The level-2 models

remain the same (Raudenbush & Bryk, 2002).

The level-1 predicted value can be transformed through a link function, usually

the logit link, where the log of the odds of success is η_{ij}:

$$\eta_{ij} = \log\left(\frac{\varphi_{ij}}{1-\varphi_{ij}}\right)$$

The level-1 structural model then becomes

$$\eta_{ij} = B_{0j} + B_{1j}X_{1j} + B_{2j}X_{2j} + ... + B_{pj}X_{pij}.$$

Student Variables

For the research questions involving academic achievement, the level one dependent variable in this study was a student's normal curve equivalent (NCE) score. Student achievement scores in each course were determined by dividing the total number of points the student earned in a course by the total number of points available in the course and using those values to create z scores. The NCE scores were calculated by converting z scores to NCE scores. Enrollments with pass/fail (S/U) grading scales and no points recorded were deleted since NCE scores could not be calculated for them.

NCE scores are similar to z scores with equal intervals maintained in the scale; however, they are normally distributed with a mean of 50 and a standard deviation of 21, and such scores range from 1 to 99. If a student had more than one NCE score, analyses included all of those. Correlations between NCE scores and continuous variables were analyzed, and variables significantly correlated with NCE scores but not with each other were chosen. SPSS and SAS were used to create the z scores, NCE scores, standard deviations, and to calculate the correlations; the NCE formula used was NCE = 50 + 21.06z.

For the achievement analysis, the independent variables at level one were age (range 16 to 73), gender (0 = male, 1 = female), level in school, persistence (0 = non-completer, 1 = completer), time to complete in days (range 25 to 481 days), active

completion time (range 0 to 378 days) and prior MU online self-paced course experience (0 = no prior MU online self-paced course experience, 1 = prior MU online self-paced course experience). Level in school was a categorical variable that was re-coded by using freshmen and sophomores as a reference group (0 = lower-division freshmen and sophomores, 1 = upper-division junior, senior, and graduate students). Most of the enrollments in self-paced courses were at the junior and senior level. Re-coding academic level resulted in acceptable distribution values so random sampling did not need to occur in the research design.

Two variables that denoted time to complete were created using SPSS since both were of interest. Time to complete in days, or enrollment time, was calculated as the difference between the student's course start date and the date their course grade was assigned. Enrollment time was of interest in determining the ideal length of time allotted for a self-paced course.

The University of Missouri requires students to enroll in self-paced courses each semester within a certain range of time to comply with reporting of data by registration cutoff dates, even though students may not plan to begin their coursework at the time of registration. Since many students did not start self-paced coursework right away — in fact, many waited until the last 3 months of the course to begin coursework — active completion time was also calculated, which was the difference between the actual date they submitted the first lesson and the date their course grade was assigned. Students must take at least 6 weeks from the date they submit the first assessment before taking the final exam no matter the self-paced delivery format, so the data was analyzed in its entirety.

In addition to the information collected from Mizzou Online's learning

management system, the University of Missouri's registration system, myZou, was used

to create the prior experience with MU online self-paced courses variable, by creating the

value based on past course enrollment history at MU for each student in the sample. The

learning management system data was also used to create a unique course identifier using

course and instructor information, which was used as the ID variable at level two.

Course Variables

Until fall 2014, students completed a course evaluation composed of 20 Likert

and other items when they completed an online self-paced course, either at the time they

took their final exam or when they completed their last lesson. Effective with fall 2014,

course evaluations designed by MU's Assessment Resource Center (ARC) for the online

courses were to be launched by the academic units that offered the courses; students

could still click on a course link to complete the evaluation online, but the goal was to use

common evaluation items developed by ARC for all courses offered at MU in order to

compare results with evaluations for traditional face-to-face courses. However, several

departmental staff members who launch evaluations for traditional classes may not have

understood that this was a new responsibility for the department and did not launch the

new evaluations or launched the evaluations inconsistently for the online courses

(University of Missouri Assessment Resource Center, 2015). With the academic units'

permission, the ARC may begin launching course evaluations for the online self-paced

courses in 2017. Since the number of evaluations collected for each online self-paced

course since fall 2014 was small or non-existent, data collected using the self-paced

course evaluation form submitted for summer 2014 enrollments and earlier were used in

this study.

Factor Analysis of Course Evaluation Variables

A variable denoting overall course satisfaction was calculated for each course through factor analysis after the Likert items that were reverse scored were recalculated and other data screening conducted. Using SPSS, factor analysis was conducted on the course evaluation items with principal axis factoring used as the extraction method and rotated with the Varimax rotation method. The Varimax rotation method was used because the data indicated there was a fairly strong single factor. Since the factor scores were more reliable than the course evaluation Likert scores, they were used instead to denote course satisfaction.

Aggregating Course Data

Prior to use in HLM, course data was aggregated using SPSS and unique ID as the break variable, resulting in 166 records for use at level 2. For the research questions involving like courses, delivery mode also served as an independent variable at level two, coded as $-1 = 8$ week, $0 = 16$ week, and $1 = 9$ month. In subsequent analysis of the data at level two, course satisfaction was analyzed, along with delivery mode in the last two research questions.

Analyses Proposed

Analysis for Research Question 1

One-way analysis of variance (ANOVA) with random effects was used to answer whether the online self-paced courses varied in mean achievement. The simplest hierarchical linear model, also known in HLM as the unconditional model because predictors are not specified at either level one or two (Raudenbush & Bryk, 2002), was

used to estimate the variance within and between online self-paced course groups. The intraclass coefficient (ICC) was also calculated to measure the proportion of variance in NCE achievement scores between online self-paced course groups.

In the one-way ANOVA with random effects, the outcome was predicted with the intercept, or the mean, within the level-1 units. The reliability estimate at level one was reviewed to assess whether individual student achievement scores were fairly reliable indicators of online self-paced course group means. If the p-value for the variance component of the online self-paced course group mean was significant and the groups varied significantly in these scores, the null hypothesis can be rejected, indicating that the online self-paced course groups differed significantly in achievement scores.

Analysis for Research Question 2

Results from the random-coefficient model were used to evaluate whether there was variability in the average student characteristic-achievement slopes to determine whether the student characteristics chosen for this study were significantly related to achievement within the online self-paced course groups. At the student level, or level 1, how much the within-course variance was reduced by adding student characteristics as predictors of academic achievement was analyzed, specifically the proportion reduction in variance at the student level, to account for any percentage of the true between-student characteristics group variance in achievement. Reliability estimates and p-values were reviewed to determine whether the model should be trimmed, removing predictors that were not statistically significant from the model when possible to result in the most parsimonious model (Raudenbush & Bryk, 2002; Wang, Osterlind & Bergin, 2012). The random-coefficient model permitted estimation of variability in regression coefficients,

slopes and intercepts, across level-2 units, with the "full" final model, intercepts- and slopes-as-outcomes, used to model, or help predict, this variability (Raudenbush & Bryk, 2002).

Analysis for Research Questions 3 and 4

The intercepts- and slopes-as outcomes model was the statistical test used to answer those questions, using the full model, intercepts- and slopes-as-outcomes, and reviewing results to determine if student characteristics were similar across courses, and whether adding course satisfaction to the equation provided any changes of significance. Results were studied to determine whether adding course satisfaction reduced the within-group variance, accounting for any percentage of the true between-online self-paced course group variance in achievement. Reliability estimates and p-values were again reviewed to determine whether predictors that were not statistically significant could be removed.

Residual variances of the student characteristics-achievement slopes were also reviewed to determine if there was a decrease from the previous model, whether slope variation was associated with course satisfaction thus explaining any residual portion of variance, and how the conditional ICC and reliability estimates of the final model compared to those obtained by using the random-coefficient model to determine which model was the better fit.

Analysis for Research Question 5

Because the persistence variable only had two possible outcomes ($0 =$ non-completer, $1 =$ completer), the Bernouilli unconditional model was used to answer the

research question concerning whether the online self-paced courses varied in mean persistence.

Analyses for Research Questions 6-8

The Bernouilli conditional model was used to answer the research questions concerning whether student characteristics were related to persistence in online self-paced courses, whether those student characteristics were similar across courses, and whether course satisfaction significantly predicted persistence. If predictors were not statistically significant, judicious model trimming occurred.

Analyses for Research Questions 9 and 10

The same type of model fitting and trimming that occurred in research questions 1 through 8 was used to analyze "like" courses for research questions 9 and 10. HLM was used to answer the supplemental research questions 9 and 10 to determine how achievement outcomes and persistence compared in like self-paced courses of varying lengths, with and without required checkpoints. It was predicted that those who persisted and completed all of their assignments and exams had significantly higher mean achievement than those who did not.

Variable Summary

For all 10 research questions as appropriate, results using HLM were reviewed using such statistics as proportion of variance, residual variance, a conditional intraclass correlation, reliability estimates, and deviance, as well as trimming variables if needed for better model fit. As stated, after model building to answer the academic achievement research questions using NCE scores as the dependent variable, the data was analyzed to answer the persistence research questions using persistence as the dependent variable.

Age, gender, level in school, enrollment time, active completion time and prior MU

online self-paced course experience were originally proposed as independent variables

for the persistence analyses, with course/instructor again serving as the ID variable at

level two. The data was then subset to "like" courses and analyzed to answer the last two

research questions. Checkpoints were ultimately not needed as a variable in the like

courses analyses, as it was determined that the only non-internship online self-paced

courses in AY 2014 that had checkpoints were those in the 8- or 16-week format, which

meant that delivery mode sufficed as a grouping variable.

Presented in Table 3 is a summary that provides the list of variables, a description

of their use in the research design, the type of data they comprise, and their level of

measurement.

Table 3

Variable Summary

Variable	Use in research design	Type of data/scale	Level of measurement
Normal Curve Equivalent achievement score	Dependent Variable at level one, Y	Continuous	Interval, range 7 to 70
Persistence	Dependent Variable at level one, Y	Categorical (0=Non-completer and 1=Completer)	Nominal
Age	Independent Variable at level one	Continuous	Interval, range 16-73
Enrollment time: Length of time to complete course (days)	Independent Variable at level one	Continuous	Interval, range 25-481
Active completion time: Length of time from date first lesson submitted to course completion (days)	Independent Variable at level one	Continuous	Interval, range 0-378
Gender	Independent Variable at level one	Categorical (0=Male and 1=Female)	Nominal
Persistence	Also used as an Independent Variable at level one	Categorical (0=Non-completer and 1=Completer)	Nominal
Academic Level in school	Independent Variable at level one	Categorical (0=Freshman/ Sophomore and 1=Junior or Above)	Nominal
Prior MU online self-paced course experience	Independent Variable at level one	Categorical (0=No experience and 1=Prior MU online self-paced course experience)	Nominal
Course/Instructor	Initial ID Variable at level two, 166 groups, j	Categorical	Nominal
Course satisfaction	Independent Variable at level two	Continuous	Interval, range –1.78 to 2.73
Delivery Mode	Independent Variable at level two for like analyses	Categorical (–1=8 week, 0=16 week, 1=9 month)	Nominal

Once the data was checked for potential problems, reviewed graphically, and invalid records filtered out, hierarchical linear modeling (HLM) was used to evaluate the research questions. Other distance education research indicates that student-level and institutional-level factors may affect achievement, persistence, and satisfaction. Therefore, analysis was conducted at both the student and institutional levels in order to achieve a more comprehensive understanding than would a single-level approach.

Assumptions

Since one-way analysis of variance (ANOVA) with random effects was the statistical technique used to answer the first research question, examining the validity of associated assumptions occurred first (Sher, 2008) using SPSS and HLM software. The four assumptions of analysis of variance, normal distribution, linearity, independence of observations, and homoscedasticity were addressed. The most important of these criteria was whether the distribution is normally distributed. Histograms of frequency distributions for the continuous variables were reviewed in conjunction with statistical analyses involving skew and kurtosis to determine whether the continuous variables had acceptable values of skew and kurtosis within the ± 3 range. The histograms and frequency distributions of the continuous variables were reviewed to see if they generally depicted data points all along the scale, meeting the assumption of linearity, and if regularity existed for the errors above and below the regression line, meeting the assumption of homoscedasticity.

If the data was skewed or exhibited kurtosis, log scores were calculated and used, in addition to decision making involving the deletion of outliers, to obtain acceptable skewness and kurtosis scores. SPSS was used to calculate measures of central tendency,

dispersion, and distribution for prior MU online self-paced course experience, the NCE achievement scores, age, persistence, enrollment time, active completion time, and course satisfaction. Once assumptions were met, HLM was used to evaluate the research questions, reviewing *p*-values at each step before continuing to the next research question and calculating such helpful variables as the intraclass correlation coefficient, the reliability estimates, confidence intervals, plausible values, sample means, and estimates for the overall academic achievement and persistence given the variables of interest at each step.

This information was used at each step to determine if the null hypotheses of no significant difference in achievement scores and persistence might be rejected, given the use of the variables in the research design and the research questions. Depending on the research question, decisions were made regarding centering variables in HLM and controlling for student or course characteristics to view variability in the slopes. The proportion reduction in variance was calculated as appropriate to see if the introduction of additional variables into the equations using HLM explained more variance in achievement and if the model with additional variables served as a better fit for the data in each step or research question. To determine the proportion reduction in variance, the variance estimate was compared with the variance estimate from the prior model. For the research questions concerning achievement, deviance was also reviewed for significance; deviance was interpreted as how much the parameters deviate from the population and served as a way of determining the accuracy of the population estimates.

Effect sizes and correlations for models with level-1 predictors were analyzed, including cross-level interactions, and predictors were dropped unless they enhanced

prediction information (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013; Wang, Osterlind & Bergin, 2012). If fixed effects, random effects, and interactions were not statistically significant and correlations were low, predictors were dropped from the model entirely with model trimming (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013; Wang, Osterlind & Bergin, 2012). If effects or interactions were a mix of significant and nonsignificant for the same predictor, the model was adjusted accordingly to retain significant and remove nonsignificant effects and interactions (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2013; Wang, Osterlind & Bergin, 2012).

Chapter Four

Results

Enrollment Data Screening

Before analyzing the enrollment data, it was screened for out-of-range data, missing data, distributions and univariate outliers. Two enrollment records were deleted after reviewing grading options from myZou. One student had enrolled as a hearer to audit the course and did not intend to finish the course, and the second enrollment was coded as a permanent military incomplete, also with no intention of finishing the course due to military deployment. Some of the pass/fail (S/U) courses did not have grading scales/points, so 35 enrollments with pass/fail grading scales were deleted since NCE scores could not be calculated for them.

This resulted in 11,829 records for evaluation grouped into about 166 unique courses/instructors. Based on the unique course title/instructor combinations, or unique IDs used to identify records, the average number of students in each course was 153.

Regarding persistence, 53 students did not quite complete all coursework but received non-failing course grades and were coded as completers with the persistence variable, and 93 students earned their F grades and were coded as completers with the persistence variable. All other F grades, for a total of 1,026 failing grades, were non-completers; they did not finish their coursework and received failing grades. One student earned an unsatisfactory "U" grade after completing all coursework and was coded as a completer with the persistence variable. All other U grades were non-completers.

At MU, students do not have a deadline to go through the revision of records process, resulting in revisions to grades at any time, sometimes for grades received years previously. If students receive a change of grade through the revision of records process, the information is recorded in myZou, including the date the new grade was assigned. Since updated grades and completion dates for self-paced courses automatically download into the learning management system, when calculating enrollment time and active enrollment time using those new dates, erroneous completion times were calculated for 11 enrollments. For example, one student's completion time was calculated as taking 541 days, although their original course grade was assigned in 288 days. For this analysis, the date of course completion was changed back to the original course completion date for those 11 enrollments, then enrollment time and active completion time were recalculated.

At MU, students may re-enroll in the same course with the instructor's permission, particularly if they did not initially finish it successfully. Students who enroll more than once in the same self-paced course take alternate proctored exams. Instructors may decide to require the student who is re-enrolling to complete different homework assignments, revise homework assignments previously submitted using the feedback they received, or count the grades received previously on homework assignments as their grades for those assignments in the new enrollment when not all coursework was completed. With the last option, faculty may ask Mizzou Online to copy the original assignment grades and dates of submission into the re-enrollment, which caused erroneous time to completion and active completion times for five re-enrollments, since the date of first submission copied into the re-enrollment occurred prior to the re-

enrollment course start date. For those five enrollments, the first lesson submission was changed to the re-enrollment course start date, then enrollment time and active completion time were recalculated.

The five academic levels of freshman, sophomore, junior, senior, and graduate students were originally recoded using solely freshmen as a reference group. However, the data was heavily skewed toward junior/senior level enrollment, so rather than delete enrollments, a lower-division reference group was created using freshman and sophomores, which resulted in acceptable distribution values.

Enrollment Data

Out-of-range data was corrected or eliminated as also discussed in the next section about assumptions. Descriptive statistics were generated for the enrollment data, with SPSS used to calculate measures of central tendency, dispersion, and distribution for persistence, enrollment time, active completion time, age at the time of enrollment, academic level (upper/lower divisions), prior self-paced course experience, gender, and the NCE scores. The mean scores indicated that the average enrollment time was 216.66 days, or 7 months, that the average active completion time was 126.93 days, or 4 months, that the mean for persistence was 0.77, for academic level was 0.68, for prior self-paced experience was 0.55, and for gender was 0.56.

These variables were also checked for acceptable skewness and kurtosis values within the ±3 range. All had acceptable skewness and kurtosis values except age as shown in Table 4.

Table 4

Enrollment Data: Measures of Central Tendency, Dispersion, and Distribution

		Persistence	Enroll-ment Time	Active Com-pletion Time	Age	Academic Level	Prior Self-Paced Experi-ence	Gender	NCE Score
N	Valid	11829	11829	10670	11829	11829	11829	11829	11829
	Missing	0	0	1159	0	0	0	0	0
Mean		0.77	216.66	126.93	22.05	0.68	0.55	0.56	50.00
Std. Error of Mean		.004	0.68	0.67	0.04	0.004	0.01	0.01	0.19
Median		1.00	258.00	105.00	21.00	1.00	1.00	1.00	59.93
Mode		1	274	105	21	1	1	1	7.68
SD		0.42	73.45	68.84	4.49	0.47	0.50	0.50	21.06
Variance		0.18	5395.37	4738.39	20.14	0.22	0.25	0.25	443.52
Skewness		-1.25	-0.70	0.59	4.32	-0.77	-0.20	-0.22	-1.19
Std. Error of Skewness		0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Kurtosis		-0.43	-1.00	-0.76	23.20	-1.41	-1.96	-1.95	-0.24
Std. Error of Kurtosis		0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Range		1	456	378	57	1	1	1	62.35
Minimum		0	25	0	16	0	0	0	7.68
Maximum		1	481	378	73	1	1	1	70.02

As shown graphically in Figure 1, the distribution for age at the time of enrollment was leptokurtic. This illustrates that students enrolled in self-paced courses at MU are traditionally college-aged students between the ages of 19 and 24, which is quite different from the predominantly nontraditional aged population that enrolls online nationwide.

Figure 1

Age: Histogram
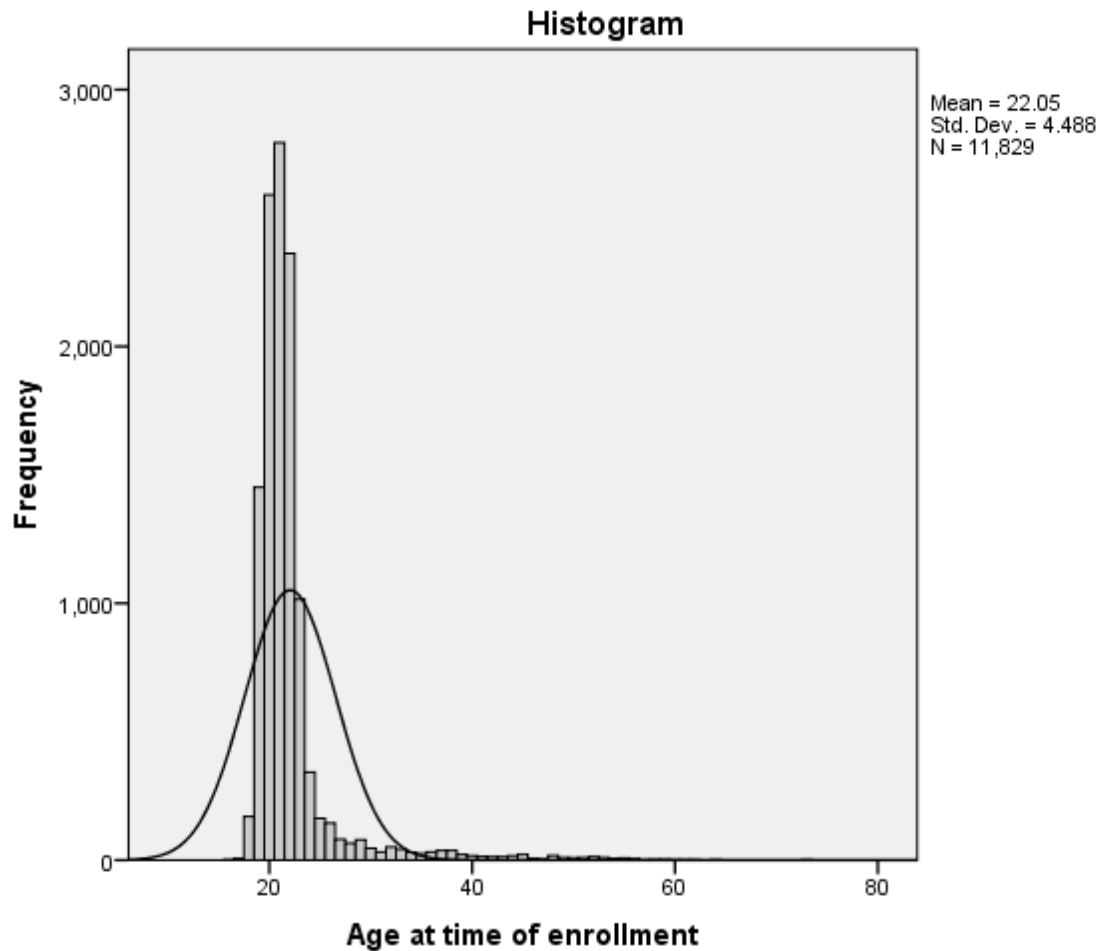
A log score for age was calculated which reduced its skew and kurtosis to 3.11 and 12.32, respectively, which were still unacceptable values. The next approach considered was random deletion of enrollments for students aged 20-22, but due to the extreme kurtosis of the data, at least half of the records for students aged 20-22 would have needed to be deleted in order for the age variable to have acceptable skew and

kurtosis. Rather than lose that amount of data, the decision was made to remove age from the analysis, since several other variables were also of interest.

Eight courses formed the basis for the last set of research questions involving "like" courses that had the same instructors, course materials, and assessments offered in more than one self-paced format or delivery mode. Of those eight "like" courses, one was offered in 8-week, 16-week, and 9-month self-paced formats and the others were offered in 16-week and 9-month formats, for a total of 20 unique course/instructor identifiers. Some of the like courses had multiple instructors teaching the multiple modalities.

Enrollment data for those 20 unique course identifiers formed a subset of 1,333 records for the last set of research questions. The average number of students in each of the like courses was 188 students. Measures of central tendency, dispersion, and distribution were calculated and reviewed for delivery mode, the new variable for those research questions, in addition to the variables previously checked for the full dataset. As before, all variables except for age in the like courses subset had acceptable skewness and kurtosis values as shown in Table 5. Creating a log score for age still resulted in unacceptable values of skew and kurtosis, resulting in a decision to also remove age as a variable from the last set of research questions for like courses.

Table 5

Enrollment Data: Measures of Central Tendency, Dispersion and Distribution for Like Courses

		Persis-tence	Enroll-ment Time	Active Com-pletion Time	Age	Aca-demic Level	Prior Self-Paced Exper-ience	Gen-der	NCE Score	Deliv-ery Mode
N	Valid	1333	1333	1231	1333	1333	1333	1333	1333	1333
	Missing	0	0	102	0	0	0	0	0	0
Mean		0.81	191.77	123.48	21.88	0.69	0.56	0.68	53.03	0.66
Std. Error of Mean		0.01	2.22	1.91	0.12	0.01	0.01	0.01	0.53	0.02
Median		1.00	194.00	102.00	21.00	1.00	1.00	1.00	61.05	1.00
Mode		1	118	81[a]	21	1	1	1	7.68	1
SD		0.39	81.06	67.00	4.20	0.46	0.50	0.47	19.35	0.56
Variance		0.15	6571.00	4489.35	17.61	0.22	0.25	0.22	374.21	0.32
Skewness		-1.60	-0.11	0.79	4.57	-0.82	-0.25	-0.75	-1.55	-1.39
Std. Error of Skewness		0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Kurtosis		0.57	-1.63	-0.44	26.33	-1.34	-1.94	-1.44	0.84	0.95
Std. Error of Kurtosis		0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Range		1	306	288	43	1	1	1	62.35	2
Minimum		0	25	8	18	0	0	0	7.68	-1
Maximum		1	331	296	61	1	1	1	70.02	1
Sum		1083	255631	152000	29171	918	749	901	70687.87	874

a. Multiple modes exist. The smallest value is shown

Once the data was checked for potential problems, reviewed graphically, and invalid records filtered out, assumptions were also checked.

Assumptions

The four assumptions of analysis of variance, normal distribution, linearity, independence of observations, and homoscedasticity, were addressed. The most important of these criteria was whether the distribution was normally distributed. Histograms of frequency distributions for the continuous variables were reviewed in

conjunction with the statistical analyses involving skew and kurtosis presented in Table

4. As stated previously, the continuous variables had acceptable values of skew and

kurtosis once age was deleted as a variable of interest. The histograms and frequency

distributions of the continuous variables generally depicted data points all along the scale,

meeting the assumption of linearity, and regularity existed for the errors above and below

the regression line, meeting the assumption of homoscedasticity. Independence of

observations was presumed. As an example, Figure 2 illustrates how enrollment times

generally clustered around a straight line, meeting these assumptions.

Figure 2

Q-Q Plot of Enrollment Time
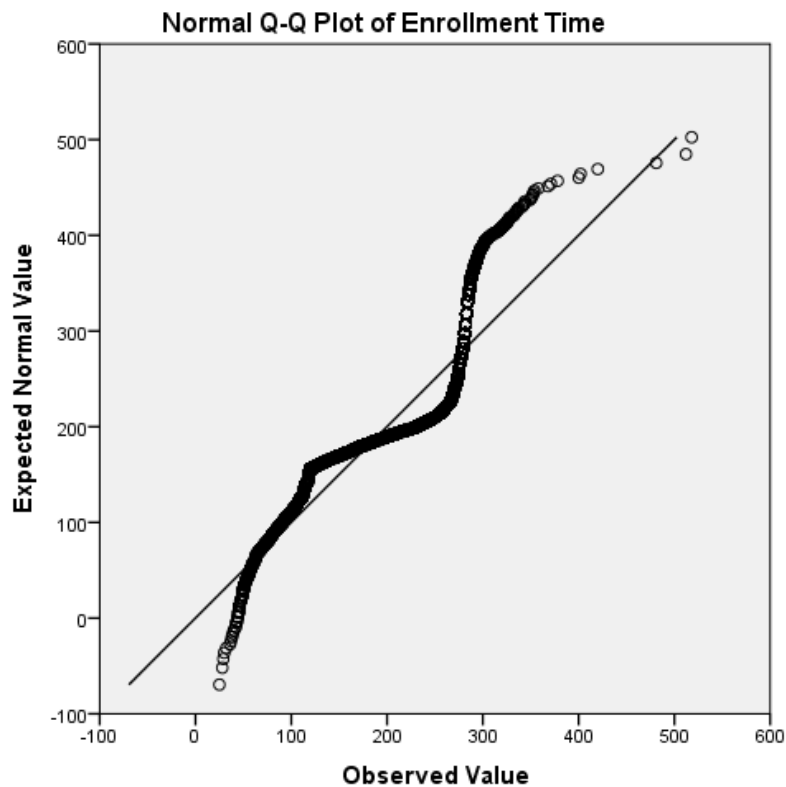
Using regression, enrollment data was checked for outliers by creating a

Mahalanobis distance variable and comparing derived values to the Mahalanobis critical

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value of 22.46 for α=.001 with six variables. Mahalanobis distances derived for 97 enrollment records exceeded the critical values, and those outliers were discarded, reducing the number of records to 11,829 enrollments for further analysis as shown earlier in Table 4.

The enrollments met the tolerance multicollinearity test with tolerance values near one. Condition indices were far less than 30, also indicating that the data was appropriate and that the independent variables did not correlate highly with each other.

Course Evaluation Data Screening

The course evaluation has been included as Appendix A; the scale is composed of 20 Likert items depicted on a 5-point continuum (1 = strongly agree, 5 = strongly disagree, N/A = does not apply), one course difficulty ranking, one overall course satisfaction grade, and seven areas for comment. Some of the Likert items on the course evaluation asked students to rate areas other than the course or instructor. For example, the first item asked students to rank whether the enrollment process was efficient.

The course evaluation file contained 3,995 records associated with the keycodes, or unique course identifiers, which matched the keycodes in the enrollment dataset. The 3-point scale for item 18 was changed to a 5-point scale to match the Likert items and the alphanumeric grades entered for item 19 were given numeric scores using a scale of 1-5 to match the Likert items (1 = "F," etc.) for a total of 22 items of interest. Some students entered comments only and left all the Likert items blank; since the Likert items are of interest in this study, 88 records with missing data for all the Likert items were deleted, leaving 3,907 records for 124 keycodes.

A frequency distribution showed that Q1, Q4, Q8, Q14, Q15, Q16, and Q27 had unacceptable kurtosis values, outside the acceptable boundaries of ±3. Answers to Likert items Q1-Q18 and Q27-Q29 were reversed so that low to high scores were associated with scores of 1-5, respectively, and out-of-range values (e.g., not applicable) were replaced with missing values. Skew and kurtosis were checked for the reversed items, with those statistics now acceptable for Q4 and Q14. However, kurtosis was still unacceptable for Q1, Q8, Q15, Q16, and Q27 because their kurtosis values were 5.02, 3.91, 4.42, 7.40, and 3.46, respectively. Inter-item correlations and scale reliability were calculated to ensure that reliability would not be affected much if those four items were deleted. Cronbach or coefficient alpha for all 22 Likert items was .95 before those three items were deleted, and .93 afterwards.

Because eliminating those items reduced reliability slightly, missing values were replaced with overall means for each item, and skew and kurtosis were re-evaluated. For the items of concern, skew and kurtosis increased somewhat, rather than decreasing. Since replacing missing values with grand means did not help the kurtosis analysis for those items, missing values were replaced with keycode group means for all 22 items and skew and kurtosis were evaluated again. This time, kurtosis values increased significantly for all four items of concern, except for a significant decrease to a kurtosis value of .30 for Q27. Rather than eliminate outlier cases entirely, because items Q1, Q8, Q15, and Q16 did not measure course satisfaction and their kurtosis values were unacceptable, those four items were left out of the factor analysis.

Q27-Q29 were items added at a later date due to a Missouri state law, resulting in a significant number of missing values for evaluations submitted prior to their addition.

Since Q27-Q29 dealt specifically with course satisfaction, they were kept for the factor analysis and missing values were replaced with keycode group means. The other items had acceptable skewness and kurtosis values. However, the range for the Likert items was five, and those values provided only weak evidence of validity due to the limited range.

Using regression, course evaluation items were checked for outliers by creating a Mahalanobis distance variable and comparing derived values to the Mahalanobis critical value of 42.31 for $\alpha=.001$ with 18 variables. Mahalanobis distances derived for 355 course evaluations exceeded the critical values, and those outliers were discarded from further analysis, reducing the number of course evaluations to 3,552.

The course evaluation items met the tolerance multicollinearity test with tolerance values near one. Condition indices were generally less than 30, also indicating that the data was appropriate and that the independent variables did not correlate highly with each other. However, toward the end of the model generated for the course evaluation items, condition indices were greater than 30, indicating problems with multicollinearity. This result occurred primarily because the range for the Likert items was small and thus there was little variance to correlate.

Statistics for the course evaluation items after data cleanup are shown in Table 6.

Table 6

Course Evaluations: Measures of Central Tendency, Dispersion and Distribution

Item	N		Mean	Std. Error of Mean	SD	Skew-ness	Std. Error of Skew-ness	Kur-tosis	Std. Error of Kur-tosis	Min	Max
	Valid	Mis-sing									
Q2	3552	0	4.27	0.02	0.87	-1.39	0.04	2.09	0.08	1	5
Q3	3552	0	4.32	0.01	0.82	-1.31	0.04	1.78	0.08	1	5
Q4	3552	0	4.36	0.01	0.74	-1.21	0.04	1.85	0.08	1	5
Q5	3552	0	4.34	0.01	0.80	-1.30	0.04	1.75	0.08	1	5
Q6	3552	0	4.35	0.01	0.84	-1.43	0.04	2.08	0.08	1	5
Q7	3552	0	4.42	0.02	0.77	-1.47	0.04	2.49	0.08	1	5
Q9	3552	0	4.29	0.01	0.85	-1.35	0.04	1.85	0.08	1	5
Q10	3552	0	4.05	0.02	1.05	-1.02	0.04	0.38	0.08	1	5
Q11	3552	0	4.18	0.02	0.96	-1.26	0.04	1.32	0.08	1	5
Q12	3552	0	4.04	0.02	1.00	-1.03	0.04	0.63	0.08	1	5
Q13	3552	0	4.14	0.02	0.97	-1.21	0.04	1.19	0.08	1	5
Q14	3552	0	4.38	0.01	0.76	-1.30	0.04	1.90	0.08	1	5
Q17	3552	0	4.32	0.01	0.84	-1.43	0.04	1.95	0.08	1	5
Q18	3552	0	4.75	0.01	0.63	-2.35	0.04	2.66	0.08	3	5
Q19	3552	0	4.40	0.01	0.76	-1.27	0.04	1.51	0.08	1	5
Q27	3552	0	4.01	0.02	1.09	-0.97	0.04	0.18	0.08	0	5
Q28	3552	0	4.12	0.01	0.80	-1.12	0.04	2.07	0.08	1	5
Q29	3552	0	4.18	0.01	0.76	-1.23	0.04	2.51	0.08	1	5

Assumptions

It was presumed that each student's course evaluation responses were independent of other students' course evaluation responses. The initial factor analysis for the course items was used to look at correlations and tests of assumptions. The correlation matrix for the remaining 18 course evaluation items showed some fairly high correlations (.60 or greater) for some of the course satisfaction items (Q6, Q7, Q9, Q11-Q13) and a high correlation, .81, for two of the instructor satisfaction items (Q28-Q29). Some of the

correlations were low; this mix was acceptable, since the course evaluation addressed more than one construct.

An assumption tested was whether or not the course evaluation data was distributed normally. The Kaiser-Meyer-Olkin (KMO) indicated the proportion of variance in the variables caused by underlying factors. A high value derived for KMO (close to one) indicates that factor analysis might be useful with the data; a value less than .50 signifies that factor analysis may not be useful. The KMO value derived was .94, which was greater than the critical value of .50. This signified a normal distribution and also that factor analysis was useful. Bartlett's Test of sphericity indicates whether or not the variables are unrelated, with a value less than 0.05 indicating probable significant relationships among the data. The null hypothesis assumed there was no difference between random zero correlations and the correlations in the matrix derived. In this instance, the significance value derived was 0.00; therefore, the null hypothesis was rejected, and it was concluded that there were probably significant relationships among the data.

The determinant was also calculated; the value derived was 2.21. Since values close to one are considered desirable, it was acceptable. Anti-image covariance and correlation matrices that contained partial covariances and correlations were also calculated. Values were close to zero on the off-diagonals and generally above .95 on the diagonals, which was acceptable. The diagonal values on the anti-image correlation matrix also indicated the measure of sampling for the items, with values less than .50 indicating variables that did not fit with the others. The values derived indicated the variables fit well with the others.

Course Evaluation Factor Analysis

Factor analysis was conducted on the course evaluation items with principal axis factoring used as the extraction method. The initial variance matrix was used to evaluate the factors numerically by observing which factors explained the most variance, as illustrated by the eigenvalues and cumulative percent of variance. The first three factors explained a great deal of the variance, with a cumulative percent of over 62%. There seemed to be a breaking point between factors three and four.

The number of factors in the initial matrix equaled the number of items in the analysis, in this case, 18. The factors were also evaluated graphically by reviewing a scree plot of eigenvalues. The scree plot clarified the decision; the most logical breaking point occurred between factors three and four. The initial factor analysis extracted three factors in eight iterations. Factor analysis was conducted a second time with principal axis factoring, this time with three factors and rotated with the Varimax rotation method. The Varimax rotation method was used because the total variance matrix and the scree plot indicated there was a fairly strong single factor.

The rotated factor analysis again extracted three factors in eight iterations. Q3 and Q4, items that asked students to assess Mizzou Online employees, as well as Q17 that asked how easy it was to use the website, were eliminated because they cross-loaded fairly equally on two factors, and factor analysis was conducted again. The final factor analysis results for the course evaluation items are shown in Table 7. Factor scores for the course evaluation items were saved for potential use in the HLM analysis. The first factor, which had the highest loadings for all the items, was considered the course

satisfaction factor used in the HLM analysis. A few random, disparate items had small cross-loadings on factors two and three and will not be needed in the HLM analysis.

Table 7

Final Factor Analysis of Course Evaluation Items

Item	Factor		
	1	2	3
Q13	.878		
Q6	.834		
Q7	.819		
Q12	.760		
Q11	.756		
Q29	.749	-.457	.272
Q9	.728		
Q10	.707		
Q28	.696	-.455	.309
Q19	.674		
Q5	.578	.364	
Q2	.546		
Q18	.506		-.349
Q14	.498	.359	
Q27	.425		
Extraction Method: Principal Axis Factoring.			

a. 3 factors extracted. 8 iterations required.

The unique identifier in the course evaluation dataset was course keycode, and the unique identifier in the enrollment dataset was the course title/instructor ID variable. Since each course keycode was associated with a particular course title, prior to using the course satisfaction factor scores as an independent variable in the HLM analysis, the course title/instructor ID variable was merged into the course evaluation dataset for use at level two. A few of the newer courses in the enrollment dataset did not have course evaluation data, since the Mizzou Online self-paced course evaluations ended with

summer 2014 courses. Some keycodes were created simply to document a course title or number change, with course content remaining the same.

Since course/instructor is used as the grouping variable and the level-2 file cannot contain missing data for the HLM analyses, data from like courses or grand means were inserted for 17 keycodes with missing course evaluation data. Also, a few keycodes had multiple instructors during the academic year. While it was possible to determine the appropriate unique ID for most of those course evaluations based on the dates instructor transitions occurred, since course evaluations were submitted anonymously, it was not possible to differentiate for a few course evaluations with overlapping instructors, so those course evaluation factor scores were duplicated for the associated unique IDs in the level-2 file.

Aggregating Course Variables

SPSS was used to aggregate course satisfaction using unique ID as the grouping variable. This became the level-2 file for use in the HLM analyses. Delivery mode was also retained for use at level 2 for the like courses analyses. The factor score mean for course satisfaction was –0.10 ($SD = 0.48$). For the like courses, as shown in Table 5 the delivery mode mean was 0.66 ($SD = 0.56$), indicating the majority of enrollments occurred in the 9-month format.

HLM Analyses

Descriptive statistics generated by HLM for the variables of interest using the full file are included in Table 8. Enrollment time will be used in the first set of analyses, then active completion time.

Table 8

Descriptive Statistics from HLM for the Full File

	Variable	Mean	*SD*
Student-level variables			
	PERSIST	0.77	0.42
	ENROLLME	216.66	73.45
	ACTIVE_C	126.93	68.84
	GENDER	0.56	0.50
	PRIORSP	0.55	0.50
	NCE_SCOR	50.00	21.06
	UPPER_LO	0.68	0.47
Course-level (group) variables			
	SATISFAC	-0.10	0.48

Statistical Analyses for Achievement

Analysis 1 for Research Question 1

What is the variability in achievement in online self-paced courses within and between courses; in other words, how much do courses vary in their mean achievement?

One-way analysis of variance (ANOVA) with random effects was used to answer this question.

One-way ANOVA with Random Effects

Level 1 $\quad Y_{ij} = \beta_{0j} + r_{ij}$

Level 2 $\quad \beta_{0j} = \gamma_{00} + u_{0j}$

Combined: $\quad Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

The one-way ANOVA with random effects provided initial information for variation in achievement between courses, $\hat{\tau}_{00}$, within courses, $\hat{\sigma}^2$, the grand mean point estimate, $\hat{\gamma}_{00}$, and the reliability of course sample means as estimates of their population true

means. In the one-way ANOVA with random effects, the outcome is predicted with the intercept, B_{0j}, or the mean, within the level-1 units. Because there are no level-1 or level-2 predictors specified, it is known as the empty or fully unconditional model (Raudenbush & Bryk, 2002). Outcome variance is denoted as

$$\text{Var}\left(Y_{ij}\right) = \text{Var}\left(u_{0j} + r_{ij}\right) = \tau_{00} + \sigma^2$$

Table 9 provides results from the one-way ANOVA model. The p-value in the unconditional model was significant. The estimated grand mean, or average course group mean achievement NCE score, γ_{00}, was 47.91 with a standard error of 0.77 and a 95% confidence interval of

$$47.91 \pm 1.96\left(0.77\right) = \left(46.40,\ 49.42\right)$$

Table 9

Results from the One-Way ANOVA for Achievement

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
Grand mean, $\hat{\gamma}_{00}$	47.91	0.77	62.44	164	<0.001

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_0 (between-course variance, $\hat{\tau}_{00}$)	82.84	164	3188.41	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	356.71			

Deviance	103,479.57
Number of estimated parameters	2

An estimate for the overall academic achievement in course groups was 47.91, with the confidence interval depicting the variability in academic achievement within course groups. The estimated variability in these course group means was 82.84. Without calculating the 95% confidence interval, this value indicated that the range in average achievement levels among course groups was significant. Plausible values for the course groups' means were

$$\hat{\gamma} \pm 1.96(\hat{\tau}_{00})^{1/2}$$
$$47.91 \pm 1.96(82.84)^{1/2} = (30.07,\ 65.75)$$

The course groups varied significantly in these scores, and the null hypothesis, $H_0 : \tau_{00} = 0,$ can be rejected; the course groups differed significantly in achievement scores. Using the information from Table 11, the reliability of the sample mean was calculated as

$$\hat{\lambda}_j = \frac{\hat{\tau}_{00}}{\left[\hat{\tau}_{00} + \left(\sigma^2/n_j\right)\right]}$$
$$\hat{\lambda} = \sum \hat{\lambda}_j/J$$
$$\hat{\lambda} = \frac{82.84}{82.84 + \dfrac{356.71}{166}}$$
$$\hat{\lambda} = .975.$$

Based on this value, the sample means tended to be reliable indicators of true online self-paced course group means.

The proportion of variance in achievement between the online self-paced course groups, or the intraclass correlation coefficient (ICC), was calculated to be

$$\hat{\rho} = \frac{\tau_{00}}{\left(\tau_{00} + \sigma^2\right)}$$

$$\hat{\rho} = \frac{82.84}{\left[82.84 + 356.71\right]} = .19$$

The ICC indicated that there was variability among the course groups, as approximately 19% of the variance in achievement was between course groups. If this value had been close to one, it would have indicated either large sample sizes or substantial variability among the course groups (Raudenbush & Bryk, 2002). The within-course variance estimate in Table 9, $\hat{\sigma}^2$, 356.71, indicated substantial variation among students within the course groups.

Analyses 2 and 3 for Research Question 2 Using Enrollment Time

On average, are student's persistence, enrollment time, gender, prior online self-paced course experience and academic level related to academic achievement within online self-paced courses?

The five independent variables were added at level 1 for the second analysis which used the enrollment time variable. Enrollment time was grand mean centered in the HLM analysis, an equivalent linear model. As noted previously, the range of enrollment time was substantial and did not include zero in the range; since zero was not included in the range, the intercept had no meaning. Grand mean centering of the enrollment time variable helped with these issues in the analysis, because subtracting the grand mean from the original score caused zero to now fall within the middle of the scores, while permitting the slope to remain unchanged (Raudenbush & Bryk, 2002). The model remained unconditional at level 2.

Level 1

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Persistence}) + \beta_{2j}(\text{Enrollment Time}) + \beta_{3j}(\text{Gender})$$
$$+ \beta_{4j}(\text{Prior SP Experience}) + \beta_{5j}(\text{Academic Level}) + r_{ij}$$

Level 2

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \qquad \beta_{1j} = \gamma_{10} + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \mu_{2j} \qquad \beta_{3j} = \gamma_{30} + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \mu_{4j} \qquad \beta_{5j} = \gamma_{50} + \mu_{5j}$$

Combined:
$$Y_{ij} = \gamma_{00} + \gamma_{10}\left(\text{Persistence }\right) + \gamma_{20}\left(\text{Enrollment Time}\right) + \gamma_{30}\left(\text{Gender}\right)$$
$$+ \gamma_{40}\left(\text{Prior SP Experience}\right) + \gamma_{50}\left(\text{Academic Level}\right)$$
$$+ u_{0j} + u_{1j}\left(\text{Persistence}\right) + u_{2j}\left(\text{Enrollment Time}\right) + u_{3j}\left(\text{Gender}\right)$$
$$+ u_{4j}\left(\text{Prior SP Experience}\right) + u_{5j}\left(\text{Academic Level}\right) + r_{ij}$$

Results for the initial random-coefficient model for Analysis 2 are provided in

Table 10.

Table 10

Results from the Initial Random-Coefficient Model for Analysis 2 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
Overall mean achievement, γ_{00}	14.09	0.37	37.93	164	<0.001
Mean Persistence-achievement slope, γ_{10}	46.13	0.50	91.90	164	<0.001
Mean Enrollment Time-achievement slope, γ_{20}	-0.004	0.00	-3.74	164	<0.001
Mean Gender-achievement slope, γ_{30}	0.45	0.14	3.24	164	0.001
Mean Prior SP Experience-achievement slope, γ_{40}	-0.51	0.13	-3.99	164	<0.001
Mean Academic Level-achievement slope, γ_{50}	0.42	0.15	2.86	164	0.005

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	14.63	120	622.59	<0.001
Persistence-achievement slope, u_{1j}	33.67	120	1932.38	<0.001
Enrollment time-achievement slope, u_{2j}	0.00	120	124.24	0.377
Gender-achievement slope, u_{3j}	0.61	120	177.31	<0.001
Prior SP experience-achievement slope, u_{4j}	0.24	120	149.10	0.037
Academic Level-achievement slope, u_{5j}	0.36	120	136.77	0.141
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	30.62			

Deviance	74,857.24
Number of estimated parameters	22

Fixed effects for analysis 2 using enrollment time.

Zero values for the dichotomous variables in the model were 0 = male, for gender, 0 = non-completer, for persistence, 0 = lower division for academic level, and 0 = no prior self-paced course experience. Using those values to interpret the level-1 intercept, 14.09 points represented the average achievement of that reference group, for a male lower-division non-completer with no prior online self-paced experience and an average enrollment time in a typical self-paced course.

The average effects of persistence, enrollment time, gender, prior self-paced experience, and academic level were all significant, with values of 46.13, –0.004, 0.45, -0.51, and 0.42, respectively. After controlling for persistence, enrollment time, gender, self-paced course experience, and academic level, there was variability in the slopes. On average, persistence, enrollment time, gender, prior self-paced course experience and academic level were significantly related to achievement within courses.

Students who persisted and had attained junior standing or above had higher academic achievement. Gender also had an effect on achievement. After controlling for the effects of persistence and enrollment time, females had higher achievement scores than males. Students with longer enrollment times had lower academic achievement, which was expected, since students who do not finish are assigned a course grade after the full enrollment time. Students with prior online self-paced experience also had lower academic achievement, which was unexpected.

Random effects for analysis 2 using enrollment time.

The estimated variance among the means, 14.63, was significant; highly significant differences existed among the course group means. Estimated variances of the

persistence, gender- and prior self-paced experience-achievement slopes were 33.67, 0.61, and 0.24, respectively, which were significant. Estimated variances of the enrollment time- and academic level-achievement slopes were 0.00 and 0.36, which were not significant. Chi-square statistics for the second analysis were only based on 121 of 165 units with sufficient data for computation, whereas variance components and fixed effects were based on all the data.

Regarding persistence, gender, and prior self-paced experience, we can reject the null hypothesis of no difference and inferred that on average, student persistence, gender, and prior self-paced experience were related to academic achievement, indicating a significant relationship between persistence, gender, prior self-paced experience, and academic achievement across the population of course groups. Regarding enrollment time and academic level, we fail to reject the null hypothesis of no difference and inferred that on average, student's enrollment time and academic level were not related to academic achievement within course groups; there was not a significant relationship between enrollment time, academic level, and academic achievement across the population of course groups.

As stated previously, the fixed effects of enrollment time and academic level were significant. Since the random effects of enrollment time and academic level were not significant, suggesting the same effect across course groups at level 2, the model was trimmed to exclude modeling the random effects of those variables (Tabachnick & Fidell, 2013). Results for the trimmed random-coefficient model for Analysis 3 are provided in Table 11.

Table 11

Results from the Trimmed Random-Coefficient Model for Analysis 3 Using Enrollment

Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
Overall mean achievement, γ_{00}	14.11	0.36	38.84	164	<0.001
Mean Persistence-achievement slope, γ_{10}	46.16	0.49	94.08	164	<0.001
Mean Enrollment Time-achievement slope, γ_{20}	-0.00	0.0001	-4.33	11167	<0.001
Mean Gender-achievement slope, γ_{30}	0.43	0.14	3.10	164	0.002
Mean Prior SP Experience-achievement slope, γ_{40}	-0.49	0.13	-3.79	164	<0.001
Mean Academic Level-achievement slope, γ_{50}	0.38	0.13	2.90	11167	0.004

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	13.92	148	872.38	<0.001
Persistence-achievement slope, u_{1j}	32.01	148	2139.10	<0.001
Gender-achievement slope, u_{3j}	0.68	148	215.26	<0.001
Prior SP experience-achievement slope, u_{4j}	0.30	148	209.10	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	30.72			

Deviance	74,878.03
Number of estimated parameters	11

Results from the Trimmed Random-Coefficient Model Using Enrollment Time

The range of plausible values for the course group means was

$$14.11 \pm 1.96(13.92)^{\frac{1}{2}} = (6.80, \ 21.42)$$

The range of plausible values for the persistence-achievement slope was

$$46.16 \pm 1.96(32.01)^{\frac{1}{2}} = (35.07, \ 57.25)$$

The range of plausible values for the gender-achievement slope was

$$0.43 \pm 1.96(0.68)^{\frac{1}{2}} = (-1.19, \ 2.05)$$

The range of plausible values for the prior self-paced experience-achievement slope was

$$-0.49 \pm 1.96(0.30)^{\frac{1}{2}} = (-1.56, \ 0.58)$$

The variance explained at level 1, or the proportion reduction in variance, was calculated by comparing the variance estimate from the first model to the trimmed random-coefficient model.

The estimated proportion of variance at level 1 explained by the random-coefficient model was

$$\frac{\hat{\sigma}^2 \left(\text{one-way ANOVA}\right) - \hat{\sigma}^2 \left(\text{random coefficient}\right)}{\hat{\sigma}^2 \left(\text{one-way ANOVA}\right)}$$

$$\left(\frac{356.71 - 30.72}{356.71}\right) = .91$$

Adding persistence, enrollment time, gender, prior self-paced experience, and academic level as predictors of achievement reduced the within-course variance by 91%. This can be interpreted as persistence, enrollment time, gender, prior self-paced experience, and academic level as accounting for 91% of the true within-course variance in achievement. Deviance decreased significantly from the fully unconditional model to the random-coefficient model, decreasing from 103,479.57 to 74,878.03 for a difference

of 28,601.54. We can reject the null hypothesis of no difference; the random-coefficient model significantly explained additional deviance and was a better fit.

Analyses 4 and 5 for Research Questions 3 and 4 Using Enrollment Time

Is the strength of association (i.e., correlational relationships) between student characteristics (gender, enrollment time, level in school, persistence, and prior online self-paced course experience) and academic achievement similar across courses, or are student characteristics more important predictors of achievement in some courses than others?

How do the online self-paced courses compare in terms of mean academic achievement and in terms of the strength of the student characteristics-achievement relationship, after controlling for course satisfaction? Does course satisfaction significantly predict achievement?

Building on the trimmed model using enrollment time in Analysis 3, course satisfaction was added at level two for Analyses 4 and 5.

Level 1

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Persistence}) + \beta_{2j}(\text{Enrollment Time}) + \beta_{3j}(\text{Gender})$$
$$+ \beta_{4j}(\text{Prior SP Experience}) + \beta_{5j}(\text{Academic Level}) + r_{ij}$$

Level 2

$$\beta_{0j} = \gamma_{00} + \gamma_{01}(\text{Satisfaction}) + \mu_{0j} \quad \beta_{1j} = \gamma_{10} + \gamma_{11}(\text{Satisfaction}) + \mu_{1j}$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}(\text{Satisfaction}) \quad\quad\quad \beta_{3j} = \gamma_{30} + \gamma_{31}(\text{Satisfaction}) + \mu_{3j}$$
$$\beta_{4j} = \gamma_{40} + \gamma_{41}(\text{Satisfaction}) + \mu_{4j} \quad \beta_{5j} = \gamma_{50} + \gamma_{51}(\text{Satisfaction})$$

Results for the initial full model using enrollment time are provided in Table 12.

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Table 12

Results from the Initial Full Model for Analysis 4 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value
Grand mean, B_{0j}					
Intercept, γ_{00}	14.05	0.38	37.32	163	<0.001
Satisfaction, γ_{01}	-0.67	0.73	-0.92	163	0.36
Effect of Persistence, B_{1j}					
Intercept, γ_{10}	46.80	0.45	105.10	163	<0.001
Satisfaction, γ_{11}	6.14	0.88	6.99	163	<0.001
Effect of Enrollment Time, B_{2j}					
Intercept, γ_{20}	-0.003	0.00	-4.04	11665	<0.001
Satisfaction, γ_{21}	0.00	0.00	0.54	11665	0.59
Effect of Gender, B_{3j}					
Intercept, γ_{30}	0.43	0.15	2.92	163	0.004
Satisfaction, γ_{31}	-0.12	0.29	-0.43	163	0.671
Effect of Prior SP Experience, B_{4j}					
Intercept, γ_{40}	-0.54	0.13	-4.07	163	<0.001
Satisfaction, γ_{41}	-0.34	0.27	-1.28	163	0.204
Effect of Academic Level, B_{5j}					
Intercept, γ_{50}	0.37	0.14	2.73	11665	0.006
Satisfaction, γ_{51}	-0.04	0.27	-0.16	11665	0.871

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	13.92	147	853.81	<0.001
Persistence-achievement slope, u_{1j}	23.28	147	1430.61	<0.001
Gender-achievement slope, u_{3j}	0.71	147	215.11	<0.001
Prior SP experience-achievement slope, u_{4j}	0.28	147	207.96	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	30.73			
Deviance	74,814.92			
Number of estimated parameters	11			

Fixed effects for analyses 4 and 5 using enrollment time.

Course satisfaction did not have a significant effect on the within-unit slopes associated with any of the level-1 student variables except for persistence, as only that cross-level interaction was significant, indicating that persistence works differently for courses with different satisfaction ratings. Nonsignificant interactions were removed from the model and the trimmed full model results are included in Table 13 for Analysis 5.

As shown in Table 13, the addition of course satisfaction into the model did not result in significant changes. There was not a significant association between course satisfaction and the average achievement of the reference group $\left(\hat{\gamma}_{01} = -0.97, \ t = -1.47\right)$. In the final trimmed model, there were six significant fixed effects on student achievement as the effects of persistence, enrollment time, gender, prior self-paced experience, and academic level were significant, as was the cross-level interaction of satisfaction with persistence. As one might logically predict, those who persist and complete the course have significantly higher mean achievement than those who do not, controlling for the effect of satisfaction. Those who persisted scored on average 46.80 more points than those who did not finish.

The negative effects of enrollment time and prior self-paced experience and the effects of gender and academic level were small but significant; as enrollment time increased by one unit, or one standard deviation, achievement *decreased* by 0.003 points. Prior self-paced experience *decreased* achievement by 0.50 point. Females scored on average 0.44 more points than males. Students with junior standing or above scored on average 0.38 more points than freshmen or sophomores.

With regard to the slopes, there was a tendency for courses with higher course

satisfaction ratings to have larger slopes than courses with lower satisfaction ratings $\left(\hat{\gamma}_{11} = 6.17, \ t = 7.05 \right)$. The hypothesis of no difference between course groups can be rejected for persistence, enrollment time, prior self-paced experience, gender, and academic level; all of those variables significantly predicted the within-course group slopes.

Table 13

Results from the Trimmed Full Model for Analysis 5 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value
Grand mean, B_{0j}					
Intercept, γ_{00}	14.01	0.37	37.45	163	<0.001
Satisfaction, γ_{01}	-0.97	0.66	-1.47	163	0.143
Effect of Persistence, B_{1j}					
Intercept, γ_{10}	46.80	0.45	105.05	163	<0.001
Satisfaction, γ_{11}	6.17	0.88	7.05	163	<0.001
Effect of Enrollment Time, B_{2j}					
Intercept, γ_{20}	-0.003	0.00	-4.23	11667	<0.001
Effect of Gender, B_{3j}					
Intercept, γ_{30}	0.44	0.14	3.12	164	0.002
Effect of Prior SP Experience, B_{4j}					
Intercept, γ_{40}	-0.50	0.13	-3.88	164	<0.001
Effect of Academic Level, B_{5j}					
Intercept, γ_{50}	0.38	0.13	2.89	11667	0.004

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	13.89	147	849.14	<0.001
Persistence-achievement slope, u_{1j}	23.30	147	1428.16	<0.001
Gender-achievement slope, u_{3j}	0.68	148	215.18	<0.001
Prior SP experience-achievement slope, u_{4j}	0.28	148	209.04	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	30.73			
Deviance	74,804.12			
Number of estimated parameters	11			

Random effects for analysis 5 using enrollment time.

Residual variance between course groups, 13.89, was slightly smaller than that in

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the trimmed random-coefficient model, 13.92. A range of plausible values for course

group means was

$$\hat{\gamma} \pm 1.96 \left(\hat{\tau}_{00} \right)^{1/2}$$
$$14.01 \pm 1.96 \left(13.89 \right)^{1/2} = \left(6.71, \ 21.31 \right)$$

After controlling for satisfaction, significant variation among course group

achievement remained to be explained. The null hypothesis for the intercepts, $H_0 : \tau_{00} = 0$

was rejected, as shown by the χ^2 statistic of 849.14, $df = 147$, $p < 0.001$.

Regarding the slopes, significant variation in the slopes also remained

unexplained after controlling for satisfaction. For example, the null hypothesis of

$H_0 : \tau_{11} = 0$ for the persistence-achievement slope was also rejected, as indicated by the

χ^2 statistic of 1428.16, $df = 147$, $p < 0.001$.

The within-course variance remained essentially the same, 30.73 in the final

trimmed full model, compared to 30.72 in the random-coefficient model. The correlation

between pairs of scores in the same course group, or a conditional intraclass correlation,

measures the degree of dependence among observations within course groups that are of

the same satisfaction levels. This conditional ICC was calculated as

$$\left(\frac{13.89}{13.89 + 30.73} \right) = .31 .$$

A reduction in deviance from the random-coefficient model to the full model

occurred; it decreased from 74,878.03 to 74,804.12, for a difference of 73.91. However,

using the variance-covariance components deviance test through the HLM program, we

fail to reject the null hypothesis of no difference; while the full model explained

additional deviance, the more parsimonious random-coefficient model was likely the better fit.

Analysis 6 for Research Question 2 Using Active Completion Time

On average, are student's persistence, active completion time, gender, prior online self-paced course experience and academic level related to academic achievement within online self-paced courses?

Analysis 6 for the second research question was conducted using active completion time, the time between the first assessment submission and the date the course grade was recorded, instead of enrollment time. The statistical notation was otherwise the same as shown for analysis 2. The five independent variables were added at level one for analysis 6. There were 1,159 enrollments in which students either did not submit any assessments or the initial assessments were removed by the instructor as incomplete without the students resuming coursework before the course grade was assigned. Those enrollments were excluded by HLM from the analysis.

Active completion time was grand mean centered in the HLM analysis. As illustrated previously, the range of active completion time was substantial. Grand mean centering of active completion time helped with this issue in the analysis. Results for the random-coefficient model for the sixth analysis using active completion time are provided in Table 14.

Table 14

Results from the Random-Coefficient Model for Analysis 6 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
Overall mean achievement, γ_{00}	19.38	0.53	36.88	164	<0.001
Mean Persistence-achievement slope, γ_{10}	40.86	0.58	70.42	164	<0.001
Mean Active Completion Time-achievement slope, γ_{20}	0.01	0.00	5.42	164	<0.001
Mean Gender-achievement slope, γ_{30}	0.31	0.15	2.03	164	0.044
Mean Prior SP Experience-achievement slope, γ_{40}	-0.61	0.13	-4.70	164	<0.001
Mean Academic Level-achievement slope, γ_{50}	0.57	0.17	3.27	164	0.001

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	30.66	122	1019.95	<0.001
Persistence-achievement slope, u_{1j}	41.66	122	1880.01	<0.001
Active Completion time-achievement slope, u_{2j}	0.00003	122	178.50	<0.001
Gender-achievement slope, u_{3j}	1.08	122	220.66	<0.001
Prior SP experience-achievement slope, u_{4j}	0.35	122	163.15	0.008
Academic Level-achievement slope, u_{5j}	1.16	122	181.50	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	26.00			

Deviance	66,011.58
Number of estimated parameters	22

Fixed effects for analysis 6 using active completion time.

Using the reference group set up previously for a male lower-division non-completer with no prior online self-paced course experience and an average active completion time in a typical self-paced course, the level-1 intercept, 19.38 points, represented the average achievement of that reference group. The average effects of persistence, active completion time, gender, prior self-paced experience, and academic level were all significant, with values of 40.86, 0.01, 0.31, -0.61, and 0.57, respectively. On average, persistence, active completion time, gender, prior self-paced course experience and academic level were significantly related to achievement within courses.

Students who persisted and had attained junior standing or above had higher academic achievement. Gender also had an effect on achievement, with females having higher achievement scores than males, although the difference was smaller than in the enrollment time analysis. Students with longer active completion times had slightly higher academic achievement, an interesting change from the negative impact of longer enrollment times. Students with prior online self-paced experience again had lower academic achievement.

Random effects for analysis 6 using active completion time.

The estimated variance among the means, 30.66, was significant; highly significant differences existed among the course group means. Estimated variances of the persistence-, active completion time-, gender-, prior self-paced experience-, and academic level-achievement slopes were all significant. Chi-square statistics for analysis 6 were only based on 123 of 165 units with sufficient data for computation, whereas variance components and fixed effects were based on all of the data.

We can reject the null hypothesis of no difference and inferred that on average, student persistence, active completion time, gender, prior self-paced experience and academic level were related to academic achievement, indicating a significant relationship between persistence, active completion time, gender, prior self-paced experience, academic level, and academic achievement across the population of course groups.

The range of plausible values for the course group means was

$$19.38 \pm 1.96(30.66)^{\frac{1}{2}} = (8.53, \ 30.23)$$

The range of plausible values for the persistence-achievement slope was

$$40.86 \pm 1.96(41.66)^{\frac{1}{2}} = (28.21, \ 53.51)$$

The range of plausible values for the active completion-achievement slope was

$$0.01 \pm 1.96(0.00003)^{\frac{1}{2}} = (-0.0007, \ 0.0107)$$

The range of plausible values for the gender-achievement slope was

$$0.31 \pm 1.96(1.08)^{\frac{1}{2}} = (-1.73, \ 2.35)$$

The range of plausible values for the prior self-paced experience-achievement slope was

$$-0.61 \pm 1.96(0.35)^{\frac{1}{2}} = (-1.77, \ 0.55)$$

The range of plausible values for the academic level-achievement slope was

$$0.57 \pm 1.96(1.16)^{\frac{1}{2}} = (-1.54, \ 2.68)$$

The estimated proportion of variance between course groups explained by the random-coefficient model using active completion time was

$$\left(\frac{356.71-26.00}{356.71}\right)=.93$$

Adding persistence, active completion time, gender, prior self-paced experience, and academic level as predictors of achievement reduced the within-course variance by 93%. This can be interpreted as persistence, active completion time, gender, prior self-paced experience, and academic level as accounting for 93% of the true within-course variance in achievement.

Deviance decreased significantly from the first model to the random-coefficient model, decreasing from 103,479.57 to 66,011.58 for a difference of 37,467.99. We can reject the null hypothesis of no difference; the random-coefficient model significantly explained additional deviance and was a better fit.

Analyses 7 and 8 for Research Questions 3 and 4 Using Active Completion Time

Building on the random-coefficient model using active completion time in the sixth analysis, course satisfaction was added at level 2 for analyses 7 and 8. The statistical notation was otherwise the same as shown for analysis 3. Results for the initial full model using active completion time are provided in Table 15.

All but one of the fixed effect cross-level interactions were not statistically significant. The only interaction that was significant with course satisfaction was persistence. Course satisfaction did not have a significant effect on the within-unit slopes associated with any of the level-1 student variables except for persistence, as only that cross-level interaction was significant, indicating that persistence works differently for courses with different satisfaction ratings. The nonsignificant interactions were removed from the model and the final trimmed full model results for analysis 8 are included in Table 16.

Table 15

Results from the Initial Full Model for Analysis 7 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
Grand mean, B_{0j}					
Intercept, γ_{00}	19.41	0.55	35.35	163	<0.001
Satisfaction, γ_{01}	0.25	1.05	0.24	163	0.813
Effect of Persistence, B_{1j}					
Intercept, γ_{10}	41.41	0.57	72.93	163	<0.001
Satisfaction, γ_{11}	5.20	1.10	4.74	163	<0.001
Effect of Active Completion Time, B_{2j}					
Intercept, γ_{20}	0.01	0.00	4.79	163	<0.001
Satisfaction, γ_{21}	-0.004	0.00	-1.91	163	0.057
Effect of Gender, B_{3j}					
Intercept, γ_{30}	0.32	0.16	2.04	163	0.043
Satisfaction, γ_{31}	0.06	0.32	0.18	163	0.855
Effect of Prior SP Experience, B_{4j}					
Intercept, γ_{40}	-0.65	0.13	-4.85	163	<0.001
Satisfaction, γ_{41}	-0.25	0.27	-0.90	163	0.370
Effect of Academic Level, B_{5j}					
Intercept, γ_{50}	0.55	0.18	2.99	163	0.003
Satisfaction, γ_{51}	-0.15	0.37	-0.40	163	0.686

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	30.73	121	1026.32	<0.001
Persistence-achievement slope, u_{1j}	35.43	121	1398.92	<0.001
Active Completion Time-Achievement slope, u_{2j}	0.00003	121	175.29	0.001
Gender-achievement slope, u_{3j}	1.09	121	220.09	<0.001
Prior SP experience-achievement slope, u_{4j}	0.40	121	163.49	0.006
Academic level-achievement slope, u_{5j}	1.24	121	181.49	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	26.00			

Deviance	65,940.65
Number of estimated parameters	22

Table 16

Results from the Trimmed Full Model for Analysis 8 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value
Grand mean, B_{0j}					
Intercept, γ_{00}	19.36	0.55	35.36	163	<0.001
Satisfaction, γ_{01}	0.01	1.00	0.01	163	0.994
Effect of Persistence, B_{1j}					
Intercept, γ_{10}	41.43	0.57	72.97	163	<0.001
Satisfaction, γ_{11}	5.32	1.08	4.91	163	<0.001
Effect of Active Completion Time, B_{2j}					
Intercept, γ_{20}	0.01	0.00	5.46	164	<0.001
Effect of Gender, B_{3j}					
Intercept, γ_{30}	0.31	0.15	2.06	164	0.041
Effect of Prior SP Experience, B_{4j}					
Intercept, γ_{40}	-0.62	0.13	-4.77	164	<0.001
Effect of Academic Level, B_{5j}					
Intercept, γ_{50}	0.58	0.18	3.29	164	0.001

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j} (between-course variance, $\hat{\tau}_{00}$)	30.76	121	1019.05	<0.001
Persistence-achievement slope, u_{1j}	35.47	121	1393.71	<0.001
Active Completion Time-Achievement slope, u_{2j}	0.00003	122	178.46	<0.001
Gender-achievement slope, u_{3j}	1.07	122	220.69	<0.001
Prior SP experience-achievement slope, u_{4j}	0.37	122	163.19	0.008
Academic level-achievement slope, u_{5j}	1.21	122	181.55	<0.001
level-1 effect, r (within-course variance, $\hat{\sigma}^2$)	26.00			

Deviance	65,933.68
Number of estimated parameters	22

Fixed effects for analysis 8 using active completion time.

The addition of course satisfaction into the equation did not result in significant changes. There was not a significant association between course satisfaction and the average achievement of the reference group $\left(\hat{\gamma}_{01} = 0.01,\ t = 0.01\right).$ In the final model, there were six significant fixed effects on student achievement as the effects of persistence, active completion time, academic level, gender, and prior self-paced experience were significant, as well as the cross-level interaction between satisfaction and persistence. Those who persisted scored on average 41.43 more points than those who did not finish.

The negative effect of prior self-paced experience and effects of active completion time, gender and academic level were small but significant. As active completion time increased by one unit, or one standard deviation, achievement increased by 0.01 points. Prior self-paced experience *decreased* achievement by 0.62 point. Females scored on average 0.31 more points than males. Students with junior standing or above scored on average 0.58 more points than freshmen or sophomores.

With regard to the slopes, there was a tendency for courses with higher course satisfaction ratings to have larger slopes than courses with lower satisfaction ratings $\left(\hat{\gamma}_{11} = 5.32,\ t = 4.91\right).$ The hypothesis of no difference between course groups can be rejected for persistence, active completion time, prior self-paced experience, gender, and academic level; those variables significantly predicted the within-course group slopes.

Random effects for analysis 8 using active completion time.

Residual variance between course groups, 30.76, was slightly higher than that in the random-coefficient model, 30.66. A range of plausible values for course group means is

$$\hat{\gamma} \pm 1.96 \left(\hat{\tau}_{00} \right)^{1/2}$$

$$19.36 \pm 1.96 \left(30.76 \right)^{1/2} = \left(8.48, \ 30.23 \right)$$

After controlling for satisfaction, significant variation among course group achievement remained to be explained. The null hypothesis for the intercepts, $H_0 : \tau_{00} = 0$ was rejected, as shown by the χ^2 statistic of 1019.05, $df = 121$, $p < 0.001$.

Regarding the slopes, significant variation in the slopes also remained unexplained after controlling for satisfaction. For example, the null hypothesis of $H_0 : \tau_{11} = 0$ for the persistence-achievement slope was also rejected, as indicated by the χ^2 statistic of 1393.71, $df = 121$, $p < 0.001$.

The within-course variance remained the same, 26.00, in both the trimmed full model and the random-coefficient model. The correlation between pairs of scores in the same course group, or a conditional intraclass correlation, measured the degree of dependence among observations within course groups that are of the same satisfaction levels. This conditional ICC was calculated as

$$\left(\frac{30.76}{30.76 + 26.00} \right) = .54 \ .$$

A reduction in deviance from the random-coefficient model to the full model occurred; it decreased from 66,011.58 to 65,933.68, for a difference of 77.90. However, using the variance-covariance components deviance test through the HLM program, we fail to reject the null hypothesis of no difference; while the full model explained additional deviance, the more parsimonious random-coefficient model was likely the better fit.

Statistical Analyses for Persistence

Analysis 9 for Research Question 5

What is the variability in persistence in online self-paced courses within and between courses; in other words, how much do online self-paced courses vary in their mean persistence?

Bernouilli unconditional model.

$$\text{Prob}\left(PERSIST_{ij} = 1 \mid \beta_j \right) = \phi_{ij}$$

Level 1 $\qquad \log[\phi_{ij} / (1 - \phi_{ij})] = \eta_{ij}$

$$\eta_{ij} = \beta_{0j}$$

Level 2 $\qquad \beta_{0j} = \gamma_{00} + u_{0j}$

$$\eta_{ij} = \gamma_{00} + u_{0j}$$
Combined:
$$PERSIST_{ij} = \gamma_{00} + u_{0j}$$

In this model, γ_{00} was the average log-odds of persistence across self-paced course groups, and τ_{00} was the variance between course groups in course-average log-odds of persistence. The results for the Bernouilli unconditional model for persistence are shown in Table 17.

Table 17

Results from the Bernouilli Unconditional Model for Analysis 9

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	1.17	0.09	13.09	164	<0.001	3.23	(2.71, 3.86)

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j}	1.09	164	1599.71	<0.001

Estimated results were significant, $\hat{\gamma}_{00} = 1.17$ $(se = 0.09)$, $\hat{\tau}_{00} = 1.09$. For regular

students in typical self-paced courses, the expected log-odds of persistence were 1.17,

related to an odds of $\exp\{1.17\} = 3.22$, about 1 to .31, for a probability of

$$\varphi_{ij} = \frac{1}{1 + \exp\{-\eta_{ij}\}}$$

$$\varphi_{ij} = \frac{1}{1 + \exp\{-1.17\}}$$

$$\varphi_{ij} = .76$$

About 95% of the course groups would be expected to have persistence log-odds

values of B_{0j} between

$$1.17 \pm 1.96(1.09)^{1/2} = (-.88, 3.22)$$

Converted to probabilities, the range would be

$$\frac{1}{1 + \exp\{.88\}} \text{ to } \frac{1}{1 + \exp\{-3.22\}}$$

$$(.29, .96)$$

Regarding the probability of persistence, about 95% of the course groups lay between (.29, .96), a significant variation.

Analyses 10 and 11 for Research Question 6 Using Enrollment Time

On average, are student's gender, enrollment time, level in school, and prior self-paced course experience related to persistence within online self-paced courses?

Bernouilli conditional model using enrollment time.

Level 1

$$\text{Prob}\left(PERSIST_{ij} = 1 \mid \beta_j\right) = \phi_{ij}$$
$$\log[\phi_{ij} / (1 - \phi_{ij})] = \eta_{ij}$$
$$\eta_{ij} = \beta_{0j} + \beta_{1j}\left(ENROLLMENT_{ij}\right) + \beta_{2j}\left(GENDER_{ij}\right) + \beta_{3j}\left(PRIORSP_{ij}\right) + \beta_{4j}\left(UPPER\_LOWER_{ij}\right)$$

Level 2
$$\beta_{0j} = \gamma_{00} + u_{0j} \quad \beta_{1j} = \gamma_{10} + u_{1j} \quad \beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j} \quad \beta_{4j} = \gamma_{40} + u_{4j}$$

$$\eta_{ij} = PERSIST_{ij} = \gamma_{00} + y_{10}\left(ENROLLMENT_{ij}\right) + y_{20}\left(GENDER_{ij}\right) + y_{30}\left(PRIORSP_{ij}\right)$$
Combined: $+ y_{40}\left(UPPER\_LOWER_{ij}\right) + u_{0j} + u_{1j}\left(ENROLLMENT_{ij}\right) + u_{2j}\left(GENDER_{ij}\right)$
$$+ u_{3j}\left(PRIORSP_{ij}\right) + u_{4j}\left(UPPER\_LOWER_{ij}\right)$$

The results for the initial Bernouilli conditional model for persistence using enrollment time are shown in Table 18. Both the fixed and random effects of prior self-paced experience were not statistically significant. Reliability estimates for the random level-1 coefficients were calculated by the HLM program and included in the output. The reliability estimate for the random level-1 coefficient for prior self-paced experience was also very low at .07, so that variable was removed from the model. The random effect of gender was also not statistically significant and was removed from the model. The results for the Bernouilli trimmed conditional model for persistence using enrollment time are shown in Table 19.

Table 18

Results from the Bernouilli Initial Conditional Model for Analysis 10 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	0.77	0.10	7.98	164	<0.001	2.15	(1.78, 2.60)
Enrollment time-persistence slope, y_{10}	-0.01	0.00	-13.44	164	<0.001	0.99	(0.991, 0.993)
Gender-persistence slope, y_{20}	0.19	0.06	3.40	164	<0.001	1.21	(1.08, 1.35)
Prior self-paced experience-persistence slope, y_{30}	-0.003	0.06	-0.05	164	0.957	1.00	(0.89, 1.11)
Academic level-persistence slope, y_{40}	0.55	0.06	8.52	164	<0.001	1.73	(1.53, 1.97)

Random Effect	Variance Component	*d.f.*	χ^2	*p*-value
Course group mean, u_{0j}	0.80	124	338.40	<0.001
Enrollment Time-persistence slope, u_{1j}	0.00001	124	172.98	0.003
Gender-persistence slope, u_{2j}	0.04	124	131.71	0.301
Prior SP experience-persistence slope, u_{3j}	0.03	124	121.30	>0.500
Academic level-persistence slope, u_{4j}	0.08	124	149.45	0.059

Table 19

Results from the Bernouilli Trimmed Conditional Model for Analysis 11 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	0.76	0.09	8.37	164	<0.001	2.14	(1.79, 2.60)
Enrollment time-persistence slope, y_{10}	–0.01	0.00	–13.60	164	<0.001	0.99	(0.991, 0.993)
Gender-persistence slope, y_{20}	0.19	0.05	3.70	11333	<0.001	1.21	(1.09, 1.33)
Academic level-persistence slope, y_{30}	0.56	0.06	8.90	164	<0.001	1.74	(1.54, 1.97)

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j}	0.73	131	420.00	<0.001
Enrollment Time-persistence slope, u_{1j}	0.00001	131	177.75	0.004
Academic level-persistence slope, u_{3j}	0.09	131	166.80	0.019

Holding constant the random effect and other predictors, enrollment time was related to a lower log-odds of persistence, $y_{10} = -.01.$ The expected odds of persistence for students with longer enrollment times was $\exp\{-.01\} = 0.99$ times less than a student who finished more quickly. For example, comparing two otherwise similar students who differed on enrollment time by one unit or standard deviation, the odds of completion of the student with the longer enrollment time was expected to be 0.99 times the odds of completion of the student who finished more quickly.

From the descriptive statistics in Table 8, enrollment time had a standard deviation of 73.45 days. A standard deviation difference in enrollment time was related to a difference in the log-odds of persistence of $73.45*(-0.01) = -0.73,$ a relative odds of $\exp\{-0.73\} = 0.482.$ In other words, the odds of completion was 0.482 compared to those with one standard deviation lower in enrollment time. From Table 19, the expected odds of persistence for females were 1.21 times that of males, and the expected odds of persistence for juniors and above were 1.74 times that of freshmen and sophomores. The chi-square statistics were only based on 132 of 165 units with data sufficient for computation.

Analyses 12 and 13 for Research Questions 7 and 8 using Enrollment Time

Is the strength of association (i.e., correlational relationships) between student characteristics (gender, enrollment time, level in school, and prior online self-paced course experience) and persistence similar across courses, or are student characteristics more important predictors of persistence in some courses than others?

How do the online self-paced courses compare in terms of persistence and in terms of the strength of the student characteristics-persistence relationship, after controlling for course satisfaction? Does course satisfaction significantly predict persistence?

Course satisfaction was added to the Bernouilli model at level 2 for the initial full conditional persistence model for analysis 12 using enrollment time.

Bernouilli full conditional model using enrollment time.

Level 1

$$\text{Prob}\left(PERSIST_{ij} = 1 \mid \beta_j\right) = \phi_{ij}$$

$$\log[\phi_{ij} / (1 - \phi_{ij})] = \eta_{ij}$$

$$\eta_{ij} = \beta_{0j} + \beta_{1j}\left(ENROLLMENT_{ij}\right) + \beta_{2j}\left(GENDER_{ij}\right) + \beta_{3j}\left(UPPER\_LOWER_{ij}\right)$$

Level 2

$$\beta_{0j} = \gamma_{00} + y_{01}\left(SATISFAC_j\right) + u_{0j} \quad \beta_{1j} = \gamma_{10} + y_{11}\left(SATISFAC_j\right) + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + y_{21}\left(SATISFAC_j\right) + u_{2j} \quad \beta_{3j} = \gamma_{30} + y_{31}\left(SATISFAC_j\right) + u_{3j}$$

As shown in Table 20, the fixed cross-level interactions were all nonsignificant and dropped from the model for analysis 13. Those results are shown in Table 21.

Table 20

Results from the Bernouilli Initial Full Conditional Model for Analysis 12 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	0.81	0.09	8.60	163	<0.001	2.25	(1.87, 2.71)
Satisfaction, γ_{01}	0.43	0.18	2.37	163	0.019	1.54	(1.08, 2.22)
Enrollment time-persistence slope, γ_{10}	-0.01	0.00	-13.19	163	<0.001	0.99	(0.991, 0.993)
Enrollment time-satisfaction slope, γ_{11}	-0.001	0.00	-1.14	163	0.257	1.00	(0.996, 1.001)
Gender-persistence slope, γ_{20}	0.19	0.05	3.60	11332	<0.001	1.21	(1.09, 1.35)
Gender-satisfaction slope, γ_{21}	0.03	0.10	0.27	11332	0.789	1.03	(0.84, 1.26)
Academic level-persistence slope, γ_{30}	0.57	0.07	8.52	163	<0.001	1.77	(1.55, 2.03)
Academic level-satisfaction slope, γ_{31}	0.15	0.13	1.15	163	0.252	1.16	(0.90, 1.49)

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j}	0.69	130	391.40	<0.001
Enrollment Time-persistence slope, u_{1j}	0.00001	130	176.35	0.004
Academic level-persistence slope, u_{3j}	0.09	130	163.93	0.019

Table 21

Results from the Bernouilli Trimmed Full Conditional Model for Analysis 13 Using Enrollment Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	0.82	0.09	8.97	163	<0.001	2.27	(1.90, 2.72)
Satisfaction, γ_{01}	0.45	0.14	3.21	163	0.002	1.56	(1.19, 2.06)
Enrollment time-persistence slope, γ_{10}	-0.01	0.00	-13.60	164	<0.001	0.99	(0.991, 0.993)
Gender-persistence slope, γ_{20}	0.19	0.05	3.7	11333	<0.001	1.21	(1.09, 1.33)
Academic level-persistence slope, γ_{30}	0.55	0.06	8.75	164	<0.001	1.73	(1.53, 1.95)

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j}	0.69	130	392.20	<0.001
Enrollment Time-persistence slope, u_{1j}	0.00001	131	177.20	0.005
Academic level-persistence slope, u_{3j}	0.09	131	166.44	0.020

At level 2, the log-odds of persistence were related to course satisfaction holding constant other predictors, $\hat{y}_{01} = 0.45$, $t = 3.21$. From Table 8, the standard deviation for course satisfaction was 0.48. Two courses that differed one standard deviation on course satisfaction that were otherwise similar could expect to be $(0.48)*(0.45) = 0.216$ units apart in log-odds of persistence, or a relative odds of $\exp\{0.216\} = 1.24$.

The zero values for the other dichotomous variables retained in the model were

$0 =$ male, for gender, and $0 =$ freshman/sophomore, for academic level. Using those

values, a hypothesis may be set up to interpret the model as the predicted probability for a

male lower-division student. If that student had an average enrollment time and was

enrolled in a typical self-paced course, the predicted log-odds of persistence were

$y_{00} = 0.82$, for a probability of $\dfrac{1}{1 + \exp\{-0.82\}} = .69.$ Adding one unit to course

satisfaction, or one standard deviation difference, provided a predicted log-odds of

$0.82 + 0.45 = 1.27$ for a predicted probability of

$$\dfrac{1}{1 + \exp\{-1.27\}} = .78$$

Analyses 14 and 15 for Research Question 6 Using Active Completion Time

      Bernouilli conditional model using active completion time.

The results for the initial Bernouilli conditional model for persistence using active

completion time are shown in Table 22. Both the fixed and random effects of prior self-

paced experience were not statistically significant, and the reliability estimate for the

random level-1 coefficient for prior self-paced experience was very low at .06, so that

variable was removed from the model. The random effects of gender and academic level

were also nonsignificant and removed from the model. The results for the Bernouilli

trimmed conditional model for persistence using active completion time are shown in

Table 23.

Table 22

Results from the Bernouilli Initial Conditional Model for Analysis 14 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. d.f.	*p*-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	1.30	0.11	11.53	164	<0.001	3.68	(2.94, 4.59)
Active Completion time-persistence slope, y_{10}	0.002	0.00	3.93	164	<0.001	1.00	(1.001, 1.003)
Gender-persistence slope, y_{20}	0.14	0.07	1.97	164	0.051	1.15	(1.00, 1.31)
Prior self-paced experience-persistence slope, y_{30}	-0.05	0.07	-0.66	164	0.511	0.96	(0.83, 1.10)
Academic level-persistence slope, y_{40}	0.62	0.08	8.27	164	<0.001	1.87	(1.61, 2.17)

Random Effect	Variance Component	d.f.	χ^2	*p*-value
Course group mean, u_{0j}	1.11	133	374.69	<0.001
Active Completion Time-persistence slope, u_{1j}	0.00001	133	216.06	<0.001
Gender-persistence slope, u_{2j}	0.08	133	137.03	0.388
Prior SP experience-persistence slope, u_{3j}	0.04	133	106.67	>0.500
Academic level-persistence slope, u_{4j}	0.08	133	147.36	0.187

From Table 23, holding constant the random effect and other predictors, active enrollment time was related to a positive log-odds of persistence, $y_{10} = 0.002$. The expected odds of persistence for students with longer active completion times were $\exp\{.002\} = 1.002$ times higher than a student who finished in less time. Comparing two otherwise similar students who differed on active completion time by one unit or standard deviation, the odds of completion of the student with the longer active completion time was expected to be 1.002 times the odds of completion of the student who finished in less time. From the descriptive statistics in Table 8, active completion time had a standard deviation of 68.84 days. A standard deviation difference in active completion time was related to a difference in the log-odds of persistence of $68.84 * (0.002) = 0.14$, a relative odds of $\exp\{0.14\} = 1.15$. In other words, the odds of completion were 1.15 compared to those with one standard deviation lower in active completion time.

From Table 23, the expected odds of persistence for females were 1.14 times that of males, and the expected odds of persistence for juniors and above were 1.75 times that of freshmen and sophomores. The chi-square statistics were based on 162 of 165 units with data sufficient for computation. Fixed effects and variance components were based on all the data.

Table 23

Results from the Bernouilli Trimmed Conditional Model for Analysis 15 using Active Completion Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	1.32	0.11	12.03	164	<0.001	3.76	(3.02, 4.67)
Active Completion time-persistence slope, y_{10}	0.002	0.00	3.91	164	<0.001	1.00	(1.001, 1.003)
Gender-persistence slope, y_{20}	0.13	0.06	2.13	10338	0.033	1.14	(1.01, 1.29)
Academic level-persistence slope, y_{30}	0.56	0.06	8.65	10338	<0.001	1.75	(1.54, 1.99)

Random Effect	Variance Component	$d.f.$	χ^2	p-value
Course group mean, u_{0j}	1.15	161	1107.37	<0.001
Enrollment Time-persistence slope, u_{1j}	0.00001	161	240.74	<0.001

Analyses 16 and 17 for Research Questions 7 and 8 Using Active Completion Time

Bernouilli full conditional model using active completion time.

Course satisfaction was added to the Bernouilli model at level 2 for the initial full conditional persistence model for analysis 16 using active completion time. As shown in Table 24, the fixed cross-level interactions for satisfaction with active completion time, gender, and academic level were not statistically significant and dropped from the model. Those results are shown in Table 25.

Table 24

Results from the Bernouilli Initial Full Conditional Model for Analysis 16 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	1.38	0.11	12.21	163	<0.001	3.97	(3.18, 4.96)
Satisfaction, γ_{01}	0.57	0.22	2.63	163	0.009	1.77	(1.15, 2.71)
Active completion time-persistence slope, γ_{10}	0.002	0.00	3.45	163	<0.001	1.00	(1.001, 1.003)
Active completion time-satisfaction slope, γ_{11}	-0.001	0.00	-0.72	163	0.472	1.00	(0.997, 1.002)
Gender-persistence slope, γ_{20}	0.15	0.07	2.18	10336	0.029	1.16	(1.02, 1.32)
Gender-satisfaction slope, γ_{21}	0.07	0.13	0.56	10336	0.577	1.07	(0.84, 1.37)
Academic level-persistence slope, γ_{30}	0.58	0.07	8.15	10336	<0.001	1.79	(1.56, 2.07)
Academic level-satisfaction slope, γ_{31}	0.13	0.13	1.02	10336	0.310	1.14	(0.88, 1.48)

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j}	1.05	160	976.73	<0.001
Active Completion time-persistence slope, u_{1j}	0.00001	160	242.15	<0.001

Table 25

Results from the Bernouilli Trimmed Full Conditional Model for Analysis 17 Using Active Completion Time

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value	Odds ratio	Confidence Interval
Model for course group means intercept, γ_{00}	1.41	0.11	12.79	163	<0.001	4.09	(3.29, 5.08)
Satisfaction, y_{01}	0.67	0.19	3.58	163	<0.001	1.96	(1.35, 2.84)
Active completion time-persistence slope, y_{10}	0.002	0.00	4.04	164	<0.001	1.00	(1.001, 1.004)
Gender-persistence slope, y_{20}	0.13	0.06	2.14	10338	0.032	1.14	(1.01, 1.29)
Academic level-persistence slope, y_{30}	0.55	0.06	8.53	10338	<0.001	1.74	(1.53, 1.98)

Random Effect	Variance Component	d.f.	χ^2	p-value
Course group mean, u_{0j}	1.05	160	979.91	<0.001
Active Completion time-persistence slope, u_{1j}	0.00001	160	242.06	<0.001

At level 2, the log-odds of persistence were related to course satisfaction holding constant other predictors, $\hat{y}_{01} = 0.67$, $t = 3.58$. Using the standard deviation for course satisfaction from Table 10, two courses that differed one standard deviation in course satisfaction that were otherwise similar could expect to be $(0.48)*(0.67) = 0.322$ units apart in log-odds of persistence, or a relative odds of $\exp\{0.322\} = 1.38$. Using the hypothesis set up earlier to interpret the model as the predicted probability of persistence

for a male lower-division student in a typical self-paced course and an average active

completion time, the predicted log-odds of persistence were $y_{00} = 1.41$, for a probability

of $\dfrac{1}{1+\exp\{-1.41\}} = .80.$ Adding one unit to course satisfaction, or one standard deviation

difference, provided a predicted log-odds of $1.41 + 0.67 = 2.08$ for a predicted probability

of

$$\frac{1}{1+\exp\{-2.08\}} = .89.$$

Achievement Analyses for Research Question 9 for Like Courses

Supplemental analyses focused on a comparison of online self-paced courses that

had identical assessments, instructors, and materials, as indicated below. Due to the

number of models and analyses overall, the actual HLM output for each model for these

research questions is included in Appendix B. Descriptive statistics generated by HLM

for the variables of interest for just the like courses are included in Table 26. Enrollment

time was used in the first set of analyses, then active completion time.

Table 26

Descriptive Statistics from HLM for Like Courses

	Variable	Mean	SD
Student-level variables			
	PERSIST	0.81	0.39
	ENROLLME	191.77	81.06
	ACTIVE_C	123.48	67.00
	GENDER	0.68	0.47
	PRIORSP	0.56	0.50
	NCE_SCOR	53.03	19.34
	UPPER_LO	0.69	0.46
Course-level (group) variables			
	SATISFAC	0.00	0.22
	MODE	0.55	0.60

Research Question 9

How does academic achievement compare in the 9-month maximum online self-paced courses and 16-week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

The *p*-value in the unconditional model for achievement for like courses was significant. The estimated grand mean, or average course group mean achievement NCE score, γ_{00}, wa 52.79 with a standard error of 1.99 and a 95% confidence interval of

$$52.79 \pm 1.96(1.99) = (48.89,\ 56.69)$$

Converted to a *z*-score of .13, this score exceeded those of 45% in the population. The reliability of the sample mean was calculated as

$$\hat{\lambda} = \frac{70.37}{70.37 + \dfrac{315.67}{20}}$$

$$\hat{\lambda} = .82.$$

Based on this value, the sample means tended to be reliable indicators of true online self-paced course group means. The proportion of variance in achievement between the online self-paced course groups, or the intraclass correlation coefficient (ICC), was calculated to be

$$\hat{\rho} = \frac{\tau_{00}}{\left(\tau_{00} + \sigma^2\right)}$$

$$\hat{\rho} = \frac{70.37}{\left[70.37 + 315.67\right]} = .18$$

Using the values derived from the output, the ICC for the unconditional model for like courses indicated that there was variability among the course groups, as

approximately 18% of the variance in achievement was between course groups. The within-course variance estimate, $\hat{\sigma}^2$, was quite high at 315.67, and indicated substantial variation among students within the course groups.

The Conditional Achievement Model Using Enrollment Time for Like Courses

The five independent variables were added at level one using the enrollment time variable. Enrollment time was again grand mean centered in the HLM analysis. Fixed and random effects for enrollment time, gender, prior self-paced experience and academic level were not statistically significant. The reliability estimates for the random level-1 coefficients for enrollment time, gender, prior self-paced experience and academic level were also quite low at .17, .25, .21, and .24, respectively. Therefore, the decision was made to remove those four variables from the model. Persistence remained in the model at level 1.

The estimated proportion of variance at level 1 explained by the random-coefficient model was

$$\left(\frac{315.67 - 30.62}{315.67}\right) = .90$$

Adding persistence as a predictor of achievement reduced the within-course variance by 90%. This can be interpreted as persistence as accounting for 90% of the true within-course variance in achievement. Deviance decreased significantly from the fully unconditional model to the random-coefficient model, decreasing from 11,499.57 to 8418.37 for a difference of 3081.20. We can reject the null hypothesis of no difference; the random-coefficient model significantly explained additional deviance and was a better fit.

Course satisfaction and delivery mode were then added at level 2 for the fully conditional model for achievement using enrollment time. None of the fixed or random effects were significant in the fully conditional model, so the random-coefficient model was the best fit. However, for the like courses analyses, robust standard errors were appropriate for datasets having a moderate to large number of level-2 units and the data did not meet this criterion. In addition, the reliability and chi square estimates were based on only 15 of 20 units that had sufficient data for computation.

The Conditional Achievement Model Using Active Completion Time for Like Courses

Five independent variables were then added at level 1 for the next random-coefficient model using active completion time which was again grand mean centered in the HLM analysis. 102 enrollments with missing values for active completion time were ignored by HLM during the analysis. The model improved with the use of active completion time compared to enrollment time as only the fixed and random effects for gender and academic level were nonsignificant and removed completely from the model. The random effect of active completion time was also nonsignificant and removed. The fixed effect of prior self-paced experience was nonsignificant but the variable was retained because its random effect was significant.

The estimated proportion of variance at level-1 explained by the random-coefficient model using active enrollment time was

$$\left(\frac{315.67 - 24.92}{315.67}\right) = .92$$

Adding active completion time, persistence, and prior self-paced experience as predictors of achievement reduced the within-course variance by 92%. This can be

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interpreted as those variables accounting for 92% of the true within-course group variance in achievement. Deviance decreased significantly from the fully unconditional model to the random-coefficient model, decreasing from 11,499.57 to 7548.43 for a difference of 3951.14. We can reject the null hypothesis of no difference; the random-coefficient model significantly explained additional deviance and was a better fit.

Cour*se* satisfaction and delivery mode were then added at level 2 for the fully conditional model for achievement using active completion time. As before, none of the fixed or random effects were significant in the fully conditional model for like courses, so the random-coefficient model was the best fit.

Persistence Analyses for Research Question 10 for Like Courses

Research Question 10

How does persistence compare in the 9 month maximum online self-paced courses and 16 week online self-paced courses with checkpoints that have identical instructors, assessments, and course materials?

Estimated results for the Bernouilli unconditional model for persistence indicated significance, with $\hat{\gamma}_{00} = 1.77$ $(se = 0.28)$, $\hat{\tau}_{00} = 1.34$. For a course with a typical persistence rate or random effect $u_{0j} = 0$, the expected log-odds of persistence were 1.77, related to an odds of $\exp\{1.77\} = 5.87$, about 1 to .17, for a probability of

$$\varphi_{ij} = \frac{1}{1 + \exp\{-1.77\}}$$
$$\varphi_{ij} = .85$$

About 95% of the course groups would be expected to have log-odds values of B_{0j} between

$$1.77 \pm 1.96(1.34)^{\frac{1}{2}} = (-0.50, 4.04)$$

Converting those to probabilities, the range would be

$$\frac{1}{1+\exp\{0.50\}} \text{ to } \frac{1}{1+\exp\{-4.04\}}$$

$$(.38, .98)$$

Regarding the probability of persistence, about 95% of the course groups lay

between (.38, .98), a significant variation.

The Conditional Persistence Model Using Enrollment Time for Like Courses

Enrollment time, gender, prior self-paced experience, and academic level were

then added to the Bernouilli model for like courses. Prior self-paced experience fixed and

random effects were nonsignificant, and the reliability estimate for the random level-1

coefficient for prior self-paced experience was low at .12, so prior self-paced experience

was removed from the model as well as the nonsignificant random effect of academic

level. Holding constant the random effect and other predictors, enrollment time was again

associated with a lower log-odds of persistence, $y_{10} = -.01$. As with the full model, the

expected odds of persistence for students in like courses who had longer enrollment times

were $\exp\{-.01\} = .99$ times less than a student who finished more quickly. Comparing two

otherwise similar students who differed on enrollment time by one unit or standard

deviation, the odds of completion of the student with the longer enrollment time was

expected to be 0.99 times the odds of completion of the student who finished more

quickly.

From the descriptive statistics in Table 26, enrollment time had a standard deviation of 81.06 days. A standard deviation difference in enrollment time was related to a difference in the log-odds of persistence of $81.06*(-0.01) = -0.81$, a relative odds of $\exp\{-0.81\} = 0.445$. The expected odds of persistence for females in like courses were 1.15 times that of males, and the expected odds of persistence for juniors and above were 2.17 times that of freshmen and sophomores.

Course satisfaction and delivery mode were then added to the Bernouilli model for like courses at level 2 for the initial full conditional persistence model using enrollment time. All of the fixed cross-level interactions except for the interaction of delivery mode with enrollment time were nonsignificant, so the nonsignificant interactions were dropped from the model. At level 2, the log-odds of persistence were not related to delivery mode but were positively related to course satisfaction *bordering significance* holding constant other predictors, $\hat{y}_{01} = 1.47$, $t = 2.09$, $p = 0.052$.

From the descriptive statistics in Table 26, course satisfaction had a standard deviation of 0.22. Two courses that differed one standard deviation in course satisfaction that were otherwise similar could expect to be $(0.22)*(1.47) = 0.32$ units apart in log-odds of persistence, or a relative odds of $\exp\{0.32\} = 1.38$. Using the hypothesis set up earlier to interpret the model as the predicted probability of persistence for a male lower-division student in a typical self-paced course and an average enrollment time, the predicted log-odds of persistence were $y_{00} = 2.08$, for a probability of

$$\frac{1}{1+\exp\{-2.08\}} = .89.$$ Adding one unit to course satisfaction, or one standard deviation

difference, provided a predicted log-odds of $2.08 + 1.47 = 3.55,$ for a predicted

probability of

$$\frac{1}{1 + \exp\{-3.55\}} = .97$$

The Conditional Persistence Model Using Active Completion Time for Like Courses

Active completion time, gender, prior self-paced experience, and academic level

were then added to the Bernouilli model for like courses. Prior self-paced experience

fixed and random effects were not statistically significant, and the reliability estimate for

the random level-1 coefficient for prior self-paced experience was low at .08, so prior

self-paced experience was removed from the model as well as the nonsignificant random

effects of active completion and academic level.

Holding constant the random effect and other predictors, active completion time

was again associated with a slightly higher log-odds of persistence, $y_{10} = 0.004.$ As with the

full model, the expected odds of persistence for students in like courses who took longer

to actively complete were $\exp\{0.0004\} = 1.004$ times higher than a student who finished in

less time. From the descriptive statistics in Table 26, active completion time had a

standard deviation of 67.00 days. A standard deviation difference in active completion

time was associated with a difference in the log-odds of persistence of

$67.00 * (0.004) = 0.268$ or a relative odds of $\exp\{-0.81\} = .445.$ Gender no longer had an

effect in this model. The expected odds of persistence for juniors and above were 2.19

times that of freshmen and sophomores.

Course satisfaction and delivery mode were then added to the Bernouilli model for like courses at level 2 for the initial full conditional persistence model using active completion time. At level 2, the log-odds of persistence were not related to either delivery mode or course satisfaction in the initial full conditional persistence model using active completion time. Gender and academic level fixed effects and gender random effects were not statistically significant; to see whether significance of the level-2 predictors would improve, gender and academic level were dropped from the final trimmed full conditional persistence model using active completion time. While the model improved slightly at level-2, the log-odds of persistence were still unrelated to either delivery mode or course satisfaction. The more parsimonious conditional model without any level-2 predictors therefore was the best fit in the like courses Bernouilli analyses using active completion time.

Chapter Five

Discussion

Discussion Large

Achievement findings and interpretation.

Table 27 provides information about the final achievement models for the full file

and Table 28 provides information about the statistical significance of the final models.

Table 27

Final Achievement Models for the Full File

Model	Variables
Achievement Using Enrollment Time	L1 $\text{Achievement}_{ij} = B_{0j} + B_{1j}\left(\text{persist}\right) + B_{2j}\left(\text{enroll time}\right)$ $+ B_{3j}\left(\text{gender}\right) + B_{4j}\left(\text{prior SP exp}\right) + B_{5j}\left(\text{acad level}\right) + r_{ij}$ L2 $B_{0j} = y_{00} + y_{01}\left(\text{satisfaction}\right) + u_{0j}$ $B_{1j} = y_{10} + y_{11}\left(\text{satisfaction}\right) + u_{1j}$ $B_{2j} = y_{20}$ $B_{3j} = y_{30} + u_{3j}$ $B_{4j} = y_{40} + u_{4j}$ $B_{5j} = y_{50}$
Achievement Using Active Completion Time	L1 $\text{Achievement}_{ij} = B_{0j} + B_{1j}\left(\text{persist}\right) + B_{2j}\left(\text{active completion time}\right)$ $+ B_{3j}\left(\text{gender}\right) + B_{4j}\left(\text{prior SP exp}\right) + B_{5j}\left(\text{acad level}\right) + r_{ij}$ L2 $B_{0j} = y_{00} + y_{01}\left(\text{satisfaction}\right) + u_{0j}$ $B_{1j} = y_{10} + y_{11}\left(\text{satisfaction}\right) + u_{1j}$ $B_{2j} = y_{20} + u_{2j}$ $B_{3j} = y_{30} + u_{3j}$ $B_{4j} = y_{40} + u_{4j}$ $B_{5j} = y_{50} + u_{5j}$

Table 28

Achievement Fixed Effects Statistical Significance Summary

Variables	Significant Effect Using Enrollment Time	Significant Effect Using Active Completion Time
Persistence	Y	Y
Enrollment Time	Y	-
Active Completion Time	-	Y
Gender	Y	Y
Prior Self-Paced Experience	Y	Y
Academic Level	Y	Y
Satisfaction	N	N
Cross-level interactions		
Satisfaction x Persistence	Y	Y

All six student variables – persistence, enrollment time, active completion time, gender, prior self-paced experience, and academic level – had significant effects on student achievement. As one might logically predict, those who persisted and completed the course had significantly higher mean achievement than those who did not, controlling for the effect of satisfaction. Those who persisted scored on average 46.80 more points than those who did not finish when enrollment time was used in the analysis, and 41.43 more points when active completion time was used in the analysis.

The negative effect of enrollment time was small but significant. As enrollment time increased by one unit, or one standard deviation, achievement *decreased* by 0.003 points. Because instructors do not assign course grades for students until they finish their coursework, withdraw, or reach the end of their enrollment time and need to have a course grade reported, the negative effect of enrollment time was somewhat expected, since students who do not finish coursework and never withdraw are not assigned a course grade until the end of their enrollment time.

Over 1,000 failing grades were assigned to non-completers. The majority of students receiving those failing grades either did not withdraw and received a failing grade at the end of their enrollment time, or withdrew at the end of their enrollment time and were not passing at the time of withdrawal. The number of failing grades assigned at the end of the enrollment time had a negative impact accordingly. Withdrawal deadlines also occurred near the end of the enrollment time and may have given students who are passing the course a sense that they can withdraw without any effect on their GPA if they do not finish in time, another possible contributing factor to longer enrollment times.

While the assignment of course grades to non-completers at the end of the enrollment time affected this outcome, students who have competing demands on their time or who are not self-directed may not be permitting themselves adequate time to complete coursework following course guidelines by their enrollment end date, another contributing factor. Other research indicates that students with external demands on their time may be enrolling in online courses, with competing life events such as work and family playing a possible part in lower achievement; those students may also be less concerned with good grades or have lower expectations in grade achievement (Helms, 2014). The negative effect of enrollment time on achievement seems to support this research.

As active completion time increased by one unit, or one standard deviation, achievement *increased* by 0.01 points. Prior self-paced experience *decreased* achievement, by 0.50 point when enrollment time was used in the analysis, and by 0.62 point when active completion time was used. Concerning active enrollment time, the minimum length of time that students should take to complete a self-paced course is 6

weeks from the date they submit their first assessment, and the average active completion time was about 4 months. Due to the self-regulation and self-pacing involved, taking more time actively completing coursework has a positive impact accordingly.

Further analysis is needed to determine why prior self-paced experience had a negative impact, since that outcome was unexpected and differs from other research findings related to online coursework (Wang et al., 2013). Other research indicating that prior online course withdrawal history impacts achievement and persistence may have a bearing (Cochran et al., 2014). It is possible that students who did not finish a self-paced course enrolled in the same course again without finishing it a second time. It is also possible that students finished a self-paced course and did well enough that they enrolled again but had difficulty with the new coursework. Until the data is studied in more detail, those are just a few possible scenarios that may have contributed to the negative outcome.

Females scored on average 0.44 more points than males when enrollment time was included, and 0.31 more points than males when active completion time was studied. Students with junior standing or above scored on average 0.38 more points than freshmen or sophomores using enrollment time, and 0.58 more points using active completion time. These findings appear to support other research regarding the potential impact of gender and academic level on persistence and achievement outcomes in online courses (Cochran et al., 2014; Wojciechowski & Palmer, 2005).

When active completion time was used in the model, the random effects of active completion time and academic level were significant and retained in the model, compared to removing the nonsignificant random effects of enrollment time and academic level when enrollment time was used.

With regard to the slopes, there was a tendency for courses with higher course satisfaction ratings to have larger slopes than courses with lower satisfaction ratings. However, there was not a significant association between course satisfaction and the average achievement of the reference group. After controlling for satisfaction, significant variation among course group achievement and the slopes remained to be explained.

The within-course variance remained essentially the same in the full models compared to the random-coefficient models. While the full models explained additional deviance, the random-coefficient models were the better fit. In the random-coefficient model, adding persistence, enrollment time, gender, prior self-paced experience, and academic level as predictors of achievement reduced the within-course variance by 91% when enrollment time was used, and by 93% when active completion time was used. This can be interpreted as persistence, enrollment time, active completion, time, gender, prior self-paced experience, and academic level as accounting for nearly all of the true within-course group variance in achievement. Most of the variance in achievement occurred at the student level, rather than at the course level, also suggested by the 19% initial intraclass correlation coefficient.

Persistence findings and interpretation.

Table 29 provides information about the final persistence models for the full file and Table 30 provides information about the statistical significance of each final model.

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Table 29

Final Persistence Models for the Full File

Model	Variables
Persistence Using Enrollment Time	L1 $\text{Persist}\,\eta_{ij} = B_{0j} + B_{1j}\left(\text{enroll time}\right) + B_{2j}\left(\text{gender}\right)$ $+ B_{3j}\left(\text{academic level}\right)$ L2 $B_{0j} = y_{00} + y_{01}\left(\text{satisfaction}\right) + u_{0j}$ $B_{1j} = y_{10} + u_{1j}$ $B_{2j} = y_{20}$ $B_{3j} = y_{30} + u_{3j}$
Persistence Using Active Completion Time	L1 $\text{Persist}\,\eta_{ij} = B_{0j} + B_{1j}\left(\text{active time}\right) + B_{2j}\left(\text{gender}\right)$ $+ B_{3j}\left(\text{academic level}\right)$ L2 $B_{0j} = y_{00} + y_{01}\left(\text{satisfaction}\right) + u_{0j}$ $B_{1j} = y_{10} + u_{1j}$ $B_{2j} = y_{20}$ $B_{3j} = y_{30}$

Table 30

Persistence Effects Statistical Significance Summary

Variables	Significant Effect Using Enrollment Time	Significant Effect Using Active Completion Time
Enrollment Time	Y	-
Active Completion Time	-	Y
Gender	Y	Y
Prior Self-Paced Experience	N	N
Academic Level	Y	Y
Satisfaction	Y	Y

At level 2, the log-odds of persistence were related to course satisfaction holding

constant other predictors. Using enrollment time, two courses that differed one standard

deviation on course satisfaction that were otherwise similar could expect to be

$(0.48)*(0.45) = 0.216$ units apart in log-odds of persistence, or a relative odds of

$\exp\{0.216\} = 1.24.$ Using active completion time, two courses that differed one standard

deviation in course satisfaction that were otherwise similar could expect to be

$(0.48)*(0.67) = 0.322$ units apart in log-odds of persistence, or a relative odds of

$\exp\{0.322\} = 1.38.$

The significant relationship between course satisfaction and persistence suggests

that successful interactions between students, instructors, and content in the online self-

paced courses may be occurring, maintaining satisfaction and learning. This effect may

also be reciprocal as student persistence may influence their satisfaction with their

course. Other research related to online coursework has reported primarily moderate to

high levels of student satisfaction, in part due to the freedom of learning online (Sher,

2008).

Using the hypothesis to interpret the model as the predicted probability for a male

lower-division student with an average *enrollment* time enrolled in a typical self-paced

course, the predicted log-odds of persistence were $y_{00} = 0.82,$ for a probability of

$\dfrac{1}{1+\exp\{-0.82\}} = .69.$ Using enrollment time, adding one unit to course satisfaction, or

one standard deviation difference, provided a predicted log-odds of $0.82 + 0.45 = 1.27$ for

a predicted probability of

$$\dfrac{1}{1+\exp\{-1.27\}} = .78$$

Using the hypothesis set up earlier to interpret the model as the predicted

probability of persistence for a male lower-division student in a typical self-paced course

and an average *active completion* time, the predicted log-odds of persistence were

$y_{00} = 1.41$, for a probability of $\dfrac{1}{1+\exp\{-1.41\}} = .80.$ Adding one unit to course

satisfaction, or one standard deviation difference, provided a predicted log-odds of

$1.41 + 0.67 = 2.08$ for a predicted probability of

$$\frac{1}{1+\exp\{-2.08\}} = .89.$$

Four of the five student variables used in the persistence study – enrollment time,

active completion time, gender, and academic level – had significant effects on student

persistence. Only the effects of prior self-paced experience were nonsignificant and

dropped from the models. Holding constant the random effect and other predictors,

enrollment time was related to a lower log-odds of persistence, $y_{10} = -.01.$ Comparing two

otherwise similar students who differed on enrollment time by one unit or standard

deviation, the odds of completion of the student with the longer enrollment time was

expected to be 0.99 times the odds of completion of the student who finished more

quickly. A standard deviation difference in enrollment time was related to a difference in

the log-odds of persistence of $73.45 * (-0.01) = -0.73,$ a relative odds of $\exp\{-0.73\} = .482.$

Comparing two otherwise similar students who differed on active completion time

by one unit or standard deviation, the odds of completion of the student with the longer

active completion time was expected to be 1.002 times the odds of completion of the

student who finished in less time. A standard deviation difference in active completion

time was related to a difference in the log-odds of persistence of $68.84*(0.002)=0.14,$ a

relative odds of $\exp\{0.14\}=1.15.$

Using enrollment time, the expected odds of persistence for females were 1.21

times that of males, and the expected odds of persistence for juniors and above were 1.74

times that of freshmen and sophomores. When active completion time was used, the

expected odds of persistence for females were 1.14 times that of males, and the expected

odds of persistence for juniors and above were 1.74 times that of freshmen and

sophomores. These findings appear to support other research regarding the potential

impact of gender and academic level on persistence and achievement outcomes in online

courses (Aragon & Johnson, 2008; Cochran et al., 2014).

Achievement findings and interpretation for like courses.

A summary of the statistical significance of the achievement findings for like

courses is included in Table 31.

Table 31

Achievement Fixed Effects Statistical Significance Summary for Like Courses

Variables	Significant Effect Using Enrollment Time	Significant Effect Using Active Completion Time
Persistence	Y	Y
Enrollment Time	N	-
Active Completion Time	-	Y*
Gender	N	N
Prior Self-Paced Experience	N	N
Academic Level	N	N
Satisfaction	N	N
Mode	N	N
Cross-level interactions		
Satisfaction x Persistence	N	N
Mode x Persistence	N	N

* In the model of best fit

Only persistence had a significant effect on student achievement when enrollment time was used. When active completion time was used, active completion time also had a significant effect (in the model of best fit, the random-coefficient model). As one might logically predict, those who persisted and completed the course had significantly higher mean achievement than those who did not, controlling for the effect of satisfaction. In the model of best fit, those who persisted scored on average 45.35 more points than those who did not finish when enrollment time was used in the analysis, and 38.79 more points when active completion time was used in the analysis.

In the random-coefficient model, adding persistence as a predictor of achievement reduced the within-course variance by 90% when enrollment time was used, and adding persistence and active completion time reduced the within-course variance by 92% when active completion time was used.

None of the fixed or random effects were significant in the fully conditional models, so the random-coefficient model was the best fit.

Persistence findings and interpretation for like courses.

A summary of the statistical significance of the persistence findings for like courses is included in Table 32.

Table 32

Persistence Effects Statistical Significance Summary for Like Courses

Variables	Significant Effect Using Enrollment Time	Significant Effect Using Active Completion Time
Enrollment Time	Y*	-
Active Completion Time	-	Y
Gender	N	N
Prior Self-Paced Experience	N	N
Academic Level	Y	Y*
Satisfaction	Y**	N
Mode	N	N
Cross-level interactions Enrollment time x mode	Y	-

* In the model of best fit

** Borderline at $p = 0.052$

The random-coefficient models were likely the models of best fit, especially when active completion time was used. Three of the five student variables used in the persistence study – enrollment time, active completion time, and academic level – had significant effects on student persistence in the random-coefficient models. The effects of prior self-paced experience were not statistically significant and dropped from both trimmed random-coefficient models.

Holding constant the random effect and other predictors, enrollment time was again associated with a lower log-odds of persistence, $y_{10} = -.01.$ Comparing two otherwise similar students who differed on *enrollment* time by one unit or standard deviation, the odds of completion of the student with the longer enrollment time were expected to be 0.99 times the odds of completion of the student who finished more quickly. Comparing two otherwise similar students who differed on *active completion* time by one unit or one standard deviation, the odds of completion of the student with the

longer active completion time were expected to be 1.004 times higher than the student who finished in less time.

A standard deviation difference in active completion time was related to a difference in the log-odds of persistence of $67.00*(0.004) = 0.268,$ a relative odds of $\exp\{-0.81\} = .445.$ Using enrollment time, the expected odds of persistence for females in like courses were 1.15 times that of males, and the expected odds of persistence for juniors and above were 2.17 times that of freshmen and sophomores. When active completion time was used, gender no longer had an effect, and the expected odds of persistence for juniors and above were 2.19 times that of freshmen and sophomores.

When using enrollment time, the log-odds of persistence were not related to delivery mode at level-2 but were positively related to course satisfaction *bordering* significance holding constant other predictors, $\hat{y}_{01} = 1.47,$ $t = 2.09,$ $p = 0.052.$ Two courses that differed one standard deviation in course satisfaction otherwise similar could expect to be $(0.22)*(1.47) = 0.32$ units apart in log-odds of persistence, or a relative odds of $\exp\{0.32\} = 1.38.$ Interpreting the model as the predicted probability of persistence for a male lower-division student in a typical self-paced course and an average enrollment time, the predicted log-odds of persistence were $y_{00} = 2.08$, for a probability of

$$\frac{1}{1+\exp\{-2.08\}} = .89.$$ Adding one unit to course satisfaction, or one standard deviation difference, provided a predicted log-odds of $2.08 + 1.47 = 3.55,$ for a predicted probability of

$$\frac{1}{1+\exp\{-3.55\}} = .97$$

At level 2 for like courses, the log-odds of persistence were not related to either delivery mode or course satisfaction using active completion time.

Conclusions

This study examined the impact of student and institutional characteristics on achievement and persistence in the self-paced format and extended the research in the field. The significant relationship between course satisfaction and persistence is an important finding and may contribute to student success as it suggests that successful interactions between students, instructors, and content in the online self-paced courses may be occurring, maintaining satisfaction, learning, and leading to persistence.

While many of the student variables had significant effects on achievement, the effect of persistence on achievement was largest by far. As one might logically predict, those who persisted and completed their online self-paced course had significantly higher mean achievement than those who did not. The effect of the other student variables, while significant in many cases, was small. The results indicated that the 9-month enrollment time was likely too long for students, so the decision to reduce that time frame to a 6-month enrollment time had merit based on these findings, especially since the mean for active completion was about four months.

It was also clear that students who actively take longer to work on their course have higher achievement, so enforcing a minimum time to complete a self-paced course continues to serve as a good guideline. While the average active enrollment time was four months, the average enrollment time was about seven months. Active completion time seemed to be a better measure of time related to coursework.

The negative effect of prior self-paced experience on achievement was unexpected, as prior experience should provide familiarity with the self-paced format, methodology, and expectations, thus providing an expectation to do as well or better in subsequent coursework. Further analysis of the data is needed to determine why prior self-paced experience had a negative effect on achievement. It is possible that students who did poorly or did not finish a course enrolled in the same course again and obtained the same outcomes, or successfully finished a course, enrolled again, and had difficulty with the new coursework.

While this data indicated that females and upper-division students generally scored more points than males and lower-division students, those effects were small and should be studied further. Some students enrolled in online programs at the University of Missouri are required to complete online orientations including online readiness assessments, due to the self-direction required. It is recommended that all students take an online readiness assessment or orientation before enrolling in an online course.

A strength of this study was the use of HLM to explore the effects of student and course variables on achievement and persistence. A limitation of this study concerned the online course evaluations. Course evaluations for the online self-paced courses were collected either when the student took the final exam or submitted online after the last online assessment. Historically, the response rate for course evaluations submitted online has been much lower than the response rate for course evaluations collected at the end of a face-to-face class. Data collected using an online evaluation may have been submitted primarily by students who felt strongly, either positively or negatively, about aspects of the course. Because the method of launching course

evaluations for self-paced courses has not achieved consistency, there is likely a better measure for course satisfaction.

Also, since course/instructor was used as the grouping variable and the level-2 file cannot contain missing data for the HLM analyses, data from like courses or grand means were inserted for 17 keycodes with missing course evaluation data. Course satisfaction did not serve as a strong variable at level 2, and part of the reason may be the homogeneity of entries as well as the limited range of the Likert items used to create the factor scores. Other variables may be more impactful at level 2, such as characteristics of faculty and other course characteristics. However, most of the variance for this study occurred at the student level, and between-course variance may have less importance on achievement and persistence outcomes for self-paced courses.

Another limitation of this study concerned the number of like courses available for the year that was analyzed. There was not sufficient data for that analysis, since there were only 8 unique courses offered in 20 combinations. Now that there are more 16-week online self-paced options available, more data is available for future comparative studies.

Future Research

These findings, particularly the impact of course satisfaction on persistence, the negative effect of longer enrollment times, and the positive effect of active completion times may be beneficial to student success and optimal self-paced course length, minimum and maximum completion time, and other self-paced course guidelines, with international as well as national implications due to the growth in online self-paced massive open online courses, other forms of flexible delivery and completion, and competency-based education.

As stated earlier, the data will be reviewed to determine why those with prior online self-paced experience are not achieving as expected. Research into using additional course- and faculty-level variables should be conducted, since there were not sufficient level-2 variables in this study after the course evaluation items combined to create a single factor score. Other variables at level 2 may affect achievement and persistence.

The decision was made to keep no-start enrollments in the enrollment data file for analysis if the course had a grading scale. The data will be analyzed further after removing the no-start enrollments to see if there are changes to the outcomes. Additional online self-paced 16-week courses have opened, so studying the 16-week and 6-month courses separately may also be possible, given sufficient data for each modality.

Comparisons of like courses may also be conducted if there are sufficient unique like courses offered in both 16-week and 6-month formats to evaluate. At the time this study was conducted, checkpoints were included solely in the 8- and 16-week courses but have since been added to some of the 6-month courses, which would be an interesting variable to study at the course level. And finally, this study was observational in nature and did not address causality; investigating student motivation and goal orientations may provide information about student motivation related to their self-paced coursework.

MIZZOU ONLINE COURSE EVALUATION

MizzouOnline

COURSE EVALUATION

136 Clark Hall

Columbia, MO 65211-4200

PHONE 1.800.609.3727 or 573.882.2491
FAX 573-882-6808
EMAIL mizzouonline@missouri.edu WEB online.missouri.edu

Course Name   **Key Code**   **Date**

Please tell us what you think about this course so that we can improve the quality of our courses for all students. The evaluation is anonymous. Your grade will not be affected by these ratings. Please feel free to provide as much detail as possible and to use extra paper if you wish.

Answer each of the items below with respect to your own personal experiences. Circle your choice to indicate the extent to which you agree or disagree with each statement. (1=Strongly Agree, 2=Agree, 3=Neutral, 4=Disagree, 5=Strongly Disagree, and N/A=Not Applicable)

1. The enrollment process was efficient.	1	2	3	4	5	N/A
2. I received prompt service in response to my inquiries.	1	2	3	4	5	N/A
3. The Mizzou Online employees who worked with me were courteous.	1	2	3	4	5	N/A
4. The Mizzou Online employees who worked with me were well informed.	1	2	3	4	5	N/A
5. Overall policies regarding the course were easy to understand.	1	2	3	4	5	N/A
6. The course author(s) were clear about what they expected students to learn.	1	2	3	4	5	N/A
7. The information presented in the course lessons was well organized.	1	2	3	4	5	N/A
8. Instructions for completing lessons were understandable.	1	2	3	4	5	N/A
9. Instructions for completing exams were helpful.	1	2	3	4	5	N/A
10. The feedback on my lessons or assignments was helpful.	1	2	3	4	5	N/A
11. The exams matched the lesson objectives.	1	2	3	4	5	N/A
12. My course grades are a good indicator of how much I have learned.	1	2	3	4	5	N/A

13. In general, I am satisfied with the quality of this course.   1   2   3   4 5   N/A

14. Navigation on the Mizzou Online website was straightforward.   1   2   3   4 5   N/A

15. It was easy to preview a progress evaluation using Mizzou Online's website.   1   2   3   4 5   N/A

16. It was easy to submit a lesson using Mizzou Online's website.   1   2   3   4 5   N/A

17. It was easy to request an exam using Mizzou Online's website.   1   2   3   4 5   N/A

18. How would you rate the difficulty level of this course? Please circle one.   Appropriate   Too easy   too difficult

19. Overall, what letter grade would you give Mizzou Online for the total educational experience that you received? Please circle one.   A   B   C   D   F

Please comment on the following aspects of your course. Feel free to provide as much detail as possible and to use extra paper if you wish.

A. Lesson Commentaries/Discussions

B. Progress Evaluations/Assignments

C. Exams

D. Instructor's Responses (for faculty-evaluated lessons) and/or Lesson Reports (for computer-evaluated lessons)

E. Student Services

F. Overall Impression of the Course

Additional Comments: If you have any comments or questions that were not addressed by this evaluation, or if you would like to offer any suggestions on ways to improve our courses, please do so in the space provided or on additional sheets.

The MU Campus collects evaluations of faculty responsible for delivery of all or parts of each course. Instructor ratings will be tabulated using the information provided in response to the following three questions. This information will be posted as part of the schedule of courses the next time this instructor is scheduled to teach this course. The information will be available for review by all students enrolled at MU. Thank you for providing this input.

1. The course content, including the lectures, syllabus, grading standards, and student responsibilities, was presented clearly.

Strongly agree   Agree   Neutral   Disagree   Strongly Disagree   No opinion

2. The instructor was interested in student learning.

Strongly agree   Agree   Neutral   Disagree   Strongly Disagree   No opinion

3. Considering both the possibilities and limitations of the subject matter and the course (including class size and facilities), the instructor taught effectively.

Strongly agree   Agree   Neutral   Disagree   Strongly Disagree   No opinion

If you have a question to which you would like a personal response, please contact Mizzou Online at 1-800-609-3727, via email: mizzouonline@missouri.edu, or on our Web site: http://online.missouri.edu.

APPENDIX B

HLM Output of Like Courses

NCE Score Unconditional Model for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	7 October 2016, Friday
Time:	15:19:44

Specifications for this HLM2 run

Problem Title: NCE EMPTY MODEL FOR LIKE COURSES
The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR
Summary of the model specified

Level-1 Model

$NCE\_SCOR_{ij} = \beta_{0j} + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$

Mixed Model

$NCE\_SCOR_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

Final Results - Iteration 5

Iterations stopped due to small change in likelihood function

$\sigma^2 = 315.66854$

τ
INTRCPT1,β_0 70.36656

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.890

The value of the log-likelihood function at iteration 5 = -5.749783E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	52.786989	1.988254	26.549	19	<0.001

Final estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	52.786989	1.937389	27.246	19	<0.001

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	8.38848	70.36656	19	266.76480	<0.001
level-1, r	17.76706	315.66854			

Statistics for current covariance components model

Deviance = 11499.566281

Number of estimated parameters = 2

Test of homogeneity of level-1 variance

χ^2 statistic = 511.11961

degrees of freedom = 19

p-value = 0.000

NCE Score Initial Random-Coefficient Model Using Enrollment Time

for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	7 October 2016, Friday
Time:	14:42:15

Specifications for this HLM2 run
Problem Title: NCE SECOND MODEL FOR LIKE COURSES

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR
Summary of the model specified
Level-1 Model
$NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(ENROLLME_{ij}) + \beta_{2j}*(PERSIST_{ij}) + \beta_{3j}*(GENDER\_N_{ij}) + \beta_{4j}*(PRIORSP_{ij}) + \beta_{5j}*(UPPER\_LO_{ij}) + r_{ij}$
Level-2 Model
$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$
$\beta_{4j} = \gamma_{40} + u_{4j}$
$\beta_{5j} = \gamma_{50} + u_{5j}$

ENROLLME has been centered around the grand mean.
Mixed Model
$NCE\_SCOR_{ij} = \gamma_{00}$
$+ \gamma_{10}*ENROLLME_{ij}$
$+ \gamma_{20}*PERSIST_{ij}$
$+ \gamma_{30}*GENDER\_N_{ij}$
$+ \gamma_{40}*PRIORSP_{ij}$
$+ \gamma_{50}*UPPER\_LO_{ij}$
$+ u_{0j} + u_{1j}*ENROLLME_{ij} + u_{2j}*PERSIST_{ij} + u_{3j}*GENDER\_N_{ij}$
$+ u_{4j}*PRIORSP_{ij} + u_{5j}*UPPER\_LO_{ij} + r_{ij}$

Final Results - Iteration 1003
Iterations stopped due to small change in likelihood function

$\sigma^2 = 30.09980$

τ

153

INTRCPT1,β_0	15.84740	-0.02164	-14.15005	-2.16984	1.90768	-0.74470
ENROLLME,β_1	-0.02164	0.00004	0.01553	0.00164	-0.00431	0.00251
PERSIST,β_2	-14.15005	0.01553	28.16504	0.44125	-1.43256	-3.10599
GENDER_N,β_3	-2.16984	0.00164	0.44125	0.92714	0.18193	0.30106
PRIORSP,β_4	1.90768	-0.00431	-1.43256	0.18193	0.69374	-0.31602
UPPER_LO,β_5	-0.74470	0.00251	-3.10599	0.30106	-0.31602	1.00912

τ (as correlations)

INTRCPT1,β_0	1.000	-0.899	-0.670	-0.566	0.575	-0.186
ENROLLME,β_1	-0.899	1.000	0.484	0.282	-0.857	0.413
PERSIST,β_2	-0.670	0.484	1.000	0.086	-0.324	-0.583
GENDER_N,β_3	-0.566	0.282	0.086	1.000	0.227	0.311
PRIORSP,β_4	0.575	-0.857	-0.324	0.227	1.000	-0.378
UPPER_LO,β_5	-0.186	0.413	-0.583	0.311	-0.378	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.504
ENROLLME,β_1	0.170
PERSIST,β_2	0.738
GENDER_N,β_3	0.254
PRIORSP,β_4	0.213
UPPER_LO,β_5	0.240

Note: The reliability estimates reported above are based on only 15 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 1003 = -4.206081E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	15.812019	1.128552	14.011	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.000116	0.002974	0.039	19	0.969
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	45.355934	1.370391	33.097	19	<0.001
For GENDER_N slope, β_3					
INTRCPT2, γ_{30}	0.182789	0.429589	0.425	19	0.675
For PRIORSP slope, β_4					
INTRCPT2, γ_{40}	0.211398	0.396138	0.534	19	0.600
For UPPER_LO slope, β_5					
INTRCPT2, γ_{50}	-0.045880	0.445661	-0.103	19	0.919

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	15.812019	1.077234	14.678	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.000116	0.001831	0.064	19	0.950
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	45.355934	1.325718	34.212	19	<0.001
For GENDER_N slope, β_3					
INTRCPT2, γ_{30}	0.182789	0.379318	0.482	19	0.635
For PRIORSP slope, β_4					
INTRCPT2, γ_{40}	0.211398	0.308850	0.684	19	0.502

For UPPER_LO slope, β_5					
INTRCPT2, γ_{50}	-0.045880	0.308496	-0.149	19	0.883

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	3.98088	15.84740	14	43.15481	<0.001
ENROLLME slope, u_1	0.00604	0.00004	14	11.17345	>0.500
PERSIST slope, u_2	5.30707	28.16504	14	58.93636	<0.001
GENDER_N slope, u_3	0.96288	0.92714	14	20.24149	0.122
PRIORSP slope, u_4	0.83291	0.69374	14	15.71903	0.330
UPPER_LO slope, u_5	1.00455	1.00912	14	9.69620	>0.500
level-1, r	5.48633	30.09980			

Note: The chi-square statistics reported above are based on only 15 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model

Deviance = 8412.161068

Number of estimated parameters = 22

Variance-Covariance components test

χ^2 statistic = 3087.40521

Degrees of freedom = 20

p-value = <0.001

Test of homogeneity of level-1 variance

χ^2 statistic = 76.53917

degrees of freedom = 14

p-value = 0.000

NCE Score Trimmed Random-Coefficient Model Using Enrollment Time

for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	7 October 2016, Friday
Time:	14:47:11

Specifications for this HLM2 run
Problem Title: NCE SECOND MODEL FOR LIKE COURSES ONLY ONE IV

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR

Summary of the model specified

Level-1 Model
$$NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(PERSIST_{ij}) + r_{ij}$$

Level-2 Model
$$\beta_{0j} = \gamma_{00} + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u_{1j}$$

Mixed Model
$$NCE\_SCOR_{ij} = \gamma_{00}$$
$$+ \gamma_{10}*PERSIST_{ij} + u_{0j} + u_{1j}*PERSIST_{ij} + r_{ij}$$

Final Results - Iteration 7
Iterations stopped due to small change in likelihood function

$\sigma^2 = 30.61943$

τ
INTRCPT1,β_0	15.39143	-15.84440
PERSIST,β_1	-15.84440	25.66239

τ (as correlations)
INTRCPT1,β_0	1.000	-0.797
PERSIST,β_1	-0.797	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.699
PERSIST,β_1	0.744

Note: The reliability estimates reported above are based on only 19 of 20

156

units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 7 = -4.209186E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	15.976937	1.076857	14.837	19	<0.001
For PERSIST slope, β_1					
INTRCPT2, γ_{10}	45.350326	1.316150	34.457	19	<0.001

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	15.976937	1.044636	15.294	19	<0.001
For PERSIST slope, β_1					
INTRCPT2, γ_{10}	45.350326	1.278731	35.465	19	<0.001

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	3.92319	15.39143	18	108.67157	<0.001
PERSIST slope, u_1	5.06581	25.66239	18	80.50767	<0.001
level-1, r	5.53348	30.61943			

Note: The chi-square statistics reported above are based on only 19 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model

Deviance = 8418.372743

Number of estimated parameters = 4

Variance-Covariance components test
χ^2 statistic = 3081.19354
Degrees of freedom = 2
p-value = <0.001

Test of homogeneity of level-1 variance
χ^2 statistic = 130.71118
degrees of freedom = 18
p-value = 0.000

NCE Score Full Model Using Enrollment Time for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	16:36: 4

Specifications for this HLM2 run
Problem Title: NCE FULL MODEL FOR LIKE COURSES

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR

Summary of the model specified

Level-1 Model

$NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(PERSIST_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$

$\beta_{1j} = \gamma_{10} + \gamma_{11}*(SATISFAC_j) + \gamma_{12}*(MODE_j) + u_{1j}$

Mixed Model

$NCE\_SCOR_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$
$+ \gamma_{10}*PERSIST_{ij} + \gamma_{11}*SATISFAC_j*PERSIST_{ij} + \gamma_{12}*MODE_j*PERSIST_{ij}$
$+ u_{0j} + u_{1j}*PERSIST_{ij} + r_{ij}$

Final Results - Iteration 11

Iterations stopped due to small change in likelihood function

$\sigma^2 = 30.59512$

τ

INTRCPT1,β_0	19.50559	-21.05511
PERSIST,β_1	-21.05511	27.16926

τ (as correlations)

INTRCPT1,β_0	1.000	-0.915
PERSIST,β_1	-0.915	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.735
PERSIST,β_1	0.753

Note: The reliability estimates reported above are based on only 19 of 20
units that had sufficient data for computation. Fixed effects and variance

158

components are based on all the data.
The value of the log-likelihood function at iteration 11 = -4.195388E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	16.049513	1.716228	9.352	17	<0.001
SATISFAC, γ_{01}	1.184522	5.669409	0.209	17	0.837
MODE, γ_{02}	-0.236867	2.067947	-0.115	17	0.910
For PERSIST slope, β_1					
INTRCPT2, γ_{10}	44.405982	1.941342	22.874	17	<0.001
SATISFAC, γ_{11}	7.161623	6.491118	1.103	17	0.285
MODE, γ_{12}	1.882984	2.368830	0.795	17	0.438

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	16.049513	2.172946	7.386	17	<0.001
SATISFAC, γ_{01}	1.184522	4.185904	0.283	17	0.781
MODE, γ_{02}	-0.236867	2.380674	-0.099	17	0.922
For PERSIST slope, β_1					
INTRCPT2, γ_{10}	44.405982	2.460741	18.046	17	<0.001
SATISFAC, γ_{11}	7.161623	5.077904	1.410	17	0.176
MODE, γ_{12}	1.882984	2.506685	0.751	17	0.463

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	4.41651	19.50559	16	100.52826	<0.001
PERSIST slope, u_1	5.21241	27.16926	16	87.68433	<0.001
level-1, r	5.53129	30.59512			

Note: The chi-square statistics reported above are based on only 19 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model
Deviance = 8390.775434
Number of estimated parameters = 4

Variance-Covariance components test
χ^2 statistic = 27.59457
Degrees of freedom = 0
p-value = >.500

Test of homogeneity of level-1 variance
χ^2 statistic = 130.71118
degrees of freedom = 18
p-value = 0.000

NCE Score Initial Random-Coefficient Model Using Active Completion

Time for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	7 October 2016, Friday
Time:	15:24:44

Specifications for this HLM2 run
Problem Title: NCE SECOND MODEL FOR LIKE COURSES USING ACTIVE TIME ALL IVS

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR

Summary of the model specified
    Level-1 Model
    $NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(PERSIST_{ij}) + \beta_{3j}*(GENDER\_N_{ij}) + \beta_{4j}*(PRIORSP_{ij}) + \beta_{5j}*(UPPER\_LO_{ij}) + r_{ij}$
    Level-2 Model
    $\beta_{0j} = \gamma_{00} + u_{0j}$
    $\beta_{1j} = \gamma_{10} + u_{1j}$
    $\beta_{2j} = \gamma_{20} + u_{2j}$
    $\beta_{3j} = \gamma_{30} + u_{3j}$
    $\beta_{4j} = \gamma_{40} + u_{4j}$
    $\beta_{5j} = \gamma_{50} + u_{5j}$

ACTIVE_C has been centered around the grand mean.
    Mixed Model
    $NCE\_SCOR_{ij} = \gamma_{00}$
    $+ \gamma_{10}*ACTIVE\_C_{ij}$
    $+ \gamma_{20}*PERSIST_{ij}$
    $+ \gamma_{30}*GENDER\_N_{ij}$
    $+ \gamma_{40}*PRIORSP_{ij}$
    $+ \gamma_{50}*UPPER\_LO_{ij}$
    $+ u_{0j} + u_{1j}*ACTIVE\_C_{ij} + u_{2j}*PERSIST_{ij} + u_{3j}*GENDER\_N_{ij}$
    $+ u_{4j}*PRIORSP_{ij} + u_{5j}*UPPER\_LO_{ij} + r_{ij}$

Run-time deletion has reduced the number of level-1 records to 1231

Final Results - Iteration 697
Iterations stopped due to small change in likelihood function

$\sigma^2 = 24.49267$

τ

INTRCPT1,β_0	46.98834	-0.00168	-43.29685	-3.66584	6.84627	-3.32285
ACTIVE_C,β_1	-0.00168	0.00001	0.01589	-0.00227	-0.00040	-0.00407
PERSIST,β_2	-43.29685	0.01589	57.51971	1.48044	-5.63764	-2.38732
GENDER_N,β_3	-3.66584	-0.00227	1.48044	0.83200	-0.34858	0.76192
PRIORSP,β_4	6.84627	-0.00040	-5.63764	-0.34858	1.23056	-0.76096
UPPER_LO,β_5	-3.32285	-0.00407	-2.38732	0.76192	-0.76096	1.94642

τ (as correlations)

INTRCPT1,β_0	1.000	-0.064	-0.833	-0.586	0.900	-0.347
ACTIVE_C,β_1	-0.064	1.000	0.548	-0.653	-0.094	-0.763
PERSIST,β_2	-0.833	0.548	1.000	0.214	-0.670	-0.226
GENDER_N,β_3	-0.586	-0.653	0.214	1.000	-0.344	0.599
PRIORSP,β_4	0.900	-0.094	-0.670	-0.344	1.000	-0.492
UPPER_LO,β_5	-0.347	-0.763	-0.226	0.599	-0.492	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.707
ACTIVE_C,β_1	0.114
PERSIST,β_2	0.844
GENDER_N,β_3	0.253
PRIORSP,β_4	0.340
UPPER_LO,β_5	0.376

Note: The reliability estimates reported above are based on only 15 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 697 = -3.766757E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.409384	1.824305	12.284	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.006771	0.002702	2.506	19	0.021
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.943073	1.941102	20.062	19	<0.001
For GENDER_N slope, β_3					
INTRCPT2, γ_{30}	-0.039869	0.406293	-0.098	19	0.923
For PRIORSP slope, β_4					
INTRCPT2, γ_{40}	0.146834	0.411444	0.357	19	0.725
For UPPER_LO slope, β_5					
INTRCPT2, γ_{50}	-0.052046	0.483540	-0.108	19	0.915

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.409384	1.752151	12.790	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.006771	0.002086	3.246	19	0.004
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.943073	1.874983	20.770	19	<0.001
For GENDER_N slope, β_3					

INTRCPT2, γ_{30}	-0.039869	0.371063	-0.107	19	0.916
For PRIORSP slope, β_4					
INTRCPT2, γ_{40}	0.146834	0.355747	0.413	19	0.684
For UPPER_LO slope, β_5					
INTRCPT2, γ_{50}	-0.052046	0.384580	-0.135	19	0.894

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	6.85480	46.98834	14	92.98808	<0.001
ACTIVE_C slope, u_1	0.00382	0.00001	14	9.86857	>0.500
PERSIST slope, u_2	7.58418	57.51971	14	149.28544	<0.001
GENDER_N slope, u_3	0.91214	0.83200	14	21.05993	0.100
PRIORSP slope, u_4	1.10931	1.23056	14	26.61393	0.021
UPPER_LO slope, u_5	1.39514	1.94642	14	17.00950	0.255
level-1, r	4.94901	24.49267			

Note: The chi-square statistics reported above are based on only 15 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model

Deviance = 7533.513095

Number of estimated parameters = 22

Variance-Covariance components test

χ^2 statistic = 3966.05319

Degrees of freedom = 20

p-value = <0.001

Test of homogeneity of level-1 variance

χ^2 statistic = 72.87516

degrees of freedom = 14

p-value = 0.000

NCE Score Trimmed Random-Coefficient Model Using Active Completion

Time for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	7 October 2016, Friday
Time:	15:35:51

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR

Summary of the model specified

Level-1 Model

$$NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(PERSIST_{ij}) + \beta_{3j}*(PRIORSP_{ij}) + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + u_{0j}$$
$$\beta_{1j} = \gamma_{10}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$

ACTIVE_C has been centered around the grand mean.

Mixed Model

$$NCE\_SCOR_{ij} = \gamma_{00}$$
$$+ \gamma_{10}*ACTIVE\_C_{ij}$$
$$+ \gamma_{20}*PERSIST_{ij}$$
$$+ \gamma_{30}*PRIORSP_{ij}$$
$$+ u_{0j} + u_{2j}*PERSIST_{ij} + u_{3j}*PRIORSP_{ij} + r_{ij}$$

Run-time deletion has reduced the number of level-1 records to 1231

Final Results - Iteration 211
Iterations stopped due to small change in likelihood function

$\sigma^2 = 24.91510$

τ

INTRCPT1,β_0	42.73494	-45.63949	5.95271
PERSIST,β_2	-45.63949	57.51471	-6.44426
PRIORSP,β_3	5.95271	-6.44426	0.86980

τ (as correlations)

INTRCPT1,β_0	1.000	-0.921	0.976
PERSIST,β_2	-0.921	1.000	-0.911
PRIORSP,β_3	0.976	-0.911	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.813
PERSIST,β_2	0.863
PRIORSP,β_3	0.294

Note: The reliability estimates reported above are based on only 16 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 211 = -3.774213E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.569949	1.736397	12.998	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.008288	0.002428	3.414	1170	<0.001
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.792594	1.948110	19.913	19	<0.001
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.138329	0.369490	0.374	19	0.712

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.569949	1.674214	13.481	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.008288	0.002140	3.872	1170	<0.001
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.792594	1.885907	20.570	19	<0.001
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.138329	0.339929	0.407	19	0.689

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	6.53720	42.73494	15	135.55565	<0.001
PERSIST slope, u_2	7.58385	57.51471	15	162.49158	<0.001
PRIORSP slope, u_3	0.93263	0.86980	15	28.26800	0.020
level-1, r	4.99150	24.91510			

Note: The chi-square statistics reported above are based on only 16 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model

Deviance = 7548.425085

Number of estimated parameters = 7

Variance-Covariance components test

χ^2 statistic = 3951.14120

Degrees of freedom = 5

p-value = <0.001

Test of homogeneity of level-1 variance

χ^2 statistic = 75.62766

degrees of freedom = 15

p-value = 0.000

NCE Score Full Model Using Active Completion Time for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	17: 5:17

Problem Title: NCE FULL MODEL LIKE COURSES USING ACTIVE TIME

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is NCE_SCOR

Summary of the model specified

Level-1 Model

$$NCE\_SCOR_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(PERSIST_{ij}) + \beta_{3j}*(PRIORSP_{ij}) + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}*(SATISFAC_j) + \gamma_{12}*(MODE_j)$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}*(SATISFAC_j) + \gamma_{22}*(MODE_j) + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}*(SATISFAC_j) + \gamma_{32}*(MODE_j) + u_{3j}$$

ACTIVE_C has been centered around the grand mean.

Mixed Model

$$NCE\_SCOR_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$$
$$+ \gamma_{10}*ACTIVE\_C_{ij} + \gamma_{11}*SATISFAC_j*ACTIVE\_C_{ij} + \gamma_{12}*MODE_j*ACTIVE\_C_{ij}$$
$$+ \gamma_{20}*PERSIST_{ij} + \gamma_{21}*SATISFAC_j*PERSIST_{ij} + \gamma_{22}*MODE_j*PERSIST_{ij}$$
$$+ \gamma_{30}*PRIORSP_{ij} + \gamma_{31}*SATISFAC_j*PRIORSP_{ij} + \gamma_{32}*MODE_j*PRIORSP_{ij}$$
$$+ u_{0j} + u_{2j}*PERSIST_{ij} + u_{3j}*PRIORSP_{ij} + r_{ij}$$

Run-time deletion has reduced the number of level-1 records to 1231

Iterations stopped due to small change in likelihood function

$\sigma^2 = 24.90939$

τ

INTRCPT1,β_0	52.14162	-51.95914	6.12431
PERSIST,β_2	-51.95914	57.29441	-7.09566
PRIORSP,β_3	6.12431	-7.09566	1.29915

τ (as correlations)

INTRCPT1,β_0 1.000 -0.951 0.744
PERSIST,β_2 -0.951 1.000 -0.822
PRIORSP,β_3 0.744 -0.822 1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.837
PERSIST,β_2	0.863
PRIORSP,β_3	0.370

Note: The reliability estimates reported above are based on only 16 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 31 = -3.765671E+003

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.494632	2.803439	8.024	17	<0.001
SATISFAC, γ_{01}	-4.794905	9.551187	-0.502	17	0.622
MODE, γ_{02}	0.913253	3.467011	0.263	17	0.795
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.005005	0.006490	0.771	1168	0.441
SATISFAC, γ_{11}	0.004068	0.009840	0.413	1168	0.679
MODE, γ_{12}	0.002606	0.006981	0.373	1168	0.709
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.045464	2.874830	13.234	17	<0.001
SATISFAC, γ_{21}	12.666579	9.907214	1.279	17	0.218
MODE, γ_{22}	0.571851	3.559852	0.161	17	0.874
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.043769	0.581506	0.075	17	0.941
SATISFAC, γ_{31}	0.204837	1.848409	0.111	17	0.913
MODE, γ_{32}	0.042917	0.733276	0.059	17	0.954

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	22.494632	2.663402	8.446	17	<0.001
SATISFAC, γ_{01}	-4.794905	7.446508	-0.644	17	0.528
MODE, γ_{02}	0.913253	3.532455	0.259	17	0.799
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.005005	0.004324	1.158	1168	0.247
SATISFAC, γ_{11}	0.004068	0.007073	0.575	1168	0.565
MODE, γ_{12}	0.002606	0.004959	0.525	1168	0.599
For PERSIST slope, β_2					
INTRCPT2, γ_{20}	38.045464	3.019474	12.600	17	<0.001
SATISFAC, γ_{21}	12.666579	7.119398	1.779	17	0.093
MODE, γ_{22}	0.571851	3.543354	0.161	17	0.874
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.043769	0.556951	0.079	17	0.938
SATISFAC, γ_{31}	0.204837	1.275415	0.161	17	0.874
MODE, γ_{32}	0.042917	0.646312	0.066	17	0.948

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	7.22092	52.14162	13	151.09057	<0.001
PERSIST slope, u_2	7.56931	57.29441	13	146.44724	<0.001
PRIORSP slope, u_3	1.13980	1.29915	13	28.41696	0.008
level-1, r	4.99093	24.90939			

Note: The chi-square statistics reported above are based on only 16 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Statistics for current covariance components model

Deviance = 7531.341949

Number of estimated parameters = 7

Variance-Covariance components test

χ^2 statistic = 17.08314

Degrees of freedom = 0

p-value = >.500

Test of homogeneity of level-1 variance

χ^2 statistic = 75.70261

degrees of freedom = 15

p-value = 0.000

Persistence Bernouilli Unconditional Model for Like Courses

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	14 October 2016, Friday
Time:	15:30:31

Problem Title: PERSISTENCE UNCONDITIONAL MODEL FOR LIKE COURSES

The data source for this run = PERSIST
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
Level-1 Model
$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$
$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j}$
Level-2 Model
$\beta_{0j} = \gamma_{00} + u_{0j}$

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
Mixed Model
$\eta_{ij} = \gamma_{00} + u_{0j}$
The value of the log-likelihood function at iteration 6 = -5.888414E+002
Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 5)

τ
INTRCPT1,β_0 1.34278

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.832

The value of the log-likelihood function at iteration 2 = -1.857674E+003
Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.772821	0.284113	6.240	19	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.772821	5.887440	(3.248,10.673)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.772821	0.276773	6.405	19	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.772821	5.887440	(3.298,10.511)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.15878	1.34278	19	188.67315	<0.001

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.840909E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.468989	0.275877	5.325	19	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.468989	4.344838	(2.438,7.742)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.468989	0.234273	6.270	19	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.468989	4.344838	(2.660,7.096)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Initial Conditional Model for Like Courses Using

Enrollment Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	17:54:16

Specifications for this Bernoulli HLM2 run
Problem Title: PERSISTENCE 2ND MODEL LIKE USING ENROLL TIME

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
Level-1 Model
$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$
$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ENROLLME_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(PRIORSP_{ij}) + \beta_{4j}*(UPPER\_LO_{ij})$
Level-2 Model
$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$
$\beta_{4j} = \gamma_{40} + u_{4j}$

ENROLLME has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
Mixed Model
$\eta_{ij} = \gamma_{00}$
$+ \gamma_{10}*ENROLLME_{ij}$
$+ \gamma_{20}*GENDER\_N_{ij}$
$+ \gamma_{30}*PRIORSP_{ij}$
$+ \gamma_{40}*UPPER\_LO_{ij}$

$+ u_{0j} + u_{1j}*ENROLLME_{ij} + u_{2j}*GENDER\_N_{ij} + u_{3j}*PRIORSP_{ij}$
$+ u_{4j}*UPPER\_LO_{ij}$

Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 71)

τ

INTRCPT1,β_0	0.63454	-0.00136	-0.19815	0.14876	-0.10388
ENROLLME,β_1	-0.00136	0.00002	-0.00177	-0.00022	-0.00067
GENDER_N,β_2	-0.19815	-0.00177	0.45398	-0.02129	0.05143
PRIORSP,β_3	0.14876	-0.00022	-0.02129	0.08877	-0.19352
UPPER_LO,β_4	-0.10388	-0.00067	0.05143	-0.19352	0.58220

τ (as correlations)

INTRCPT1,β_0	1.000	-0.420	-0.369	0.627	-0.171
ENROLLME,β_1	-0.420	1.000	-0.647	-0.183	-0.216
GENDER_N,β_2	-0.369	-0.647	1.000	-0.106	0.100
PRIORSP,β_3	0.627	-0.183	-0.106	1.000	-0.851
UPPER_LO,β_4	-0.171	-0.216	0.100	-0.851	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.269
ENROLLME,β_1	0.176
GENDER_N,β_2	0.345
PRIORSP,β_3	0.117
UPPER_LO,β_4	0.348

Note: The reliability estimates reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 2 = -1.867065E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.218054	0.275575	4.420	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.008880	0.001704	-5.211	19	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.092106	0.253946	0.363	19	0.721
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.017507	0.193806	0.090	19	0.929
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.676703	0.282670	2.394	19	0.027

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.218054	3.380603	(1.898,6.020)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.008880	0.991160	(0.988,0.995)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.092106	1.096482	(0.644,1.866)	
For PRIORSP slope, β_3				
INTRCPT2, γ_{30}	0.017507	1.017661	(0.678,1.527)	
For UPPER_LO slope, β_4				

	INTRCPT2, γ_{40}	0.676703	1.967380	(1.088,3.556)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.218054	0.250058	4.871	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.008880	0.001527	-5.817	19	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.092106	0.242717	0.379	19	0.709
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	0.017507	0.122477	0.143	19	0.888
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.676703	0.271947	2.488	19	0.022

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.218054	3.380603	(2.003,5.707)
For ENROLLME slope, β_1			
INTRCPT2, γ_{10}	-0.008880	0.991160	(0.988,0.994)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.092106	1.096482	(0.660,1.823)
For PRIORSP slope, β_3			
INTRCPT2, γ_{30}	0.017507	1.017661	(0.787,1.315)
For UPPER_LO slope, β_4			
INTRCPT2, γ_{40}	0.676703	1.967380	(1.113,3.477)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	0.79658	0.63454	16	44.74652	<0.001
ENROLLME slope, u_1	0.00405	0.00002	16	40.36971	<0.001
GENDER_N slope, u_2	0.67378	0.45398	16	29.89274	0.018
PRIORSP slope, u_3	0.29795	0.08877	16	10.68126	>0.500
UPPER_LO slope, u_4	0.76302	0.58220	16	23.26678	0.107

Note: The chi-square statistics reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.647348E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.023987	0.243079	4.213	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.004307	0.001373	-3.137	19	0.005
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.014450	0.216296	0.067	19	0.947

For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	-0.009136	0.151773	-0.060	19	0.953
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.380351	0.240068	1.584	19	0.130

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.023987	2.784274	(1.674,4.632)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.004307	0.995703	(0.993,0.999)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.014450	1.014555	(0.645,1.596)	
For PRIORSP slope, β_3				
INTRCPT2, γ_{30}	-0.009136	0.990906	(0.721,1.362)	
For UPPER_LO slope, β_4				
INTRCPT2, γ_{40}	0.380351	1.462798	(0.885,2.418)	

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.023987	0.190850	5.365	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.004307	0.000854	-5.043	19	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.014450	0.158443	0.091	19	0.928
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	-0.009136	0.074519	-0.123	19	0.904
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.380351	0.190153	2.000	19	0.060

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.023987	2.784274	(1.867,4.152)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.004307	0.995703	(0.994,0.997)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.014450	1.014555	(0.728,1.414)	
For PRIORSP slope, β_3				
INTRCPT2, γ_{30}	-0.009136	0.990906	(0.848,1.158)	
For UPPER_LO slope, β_4				
INTRCPT2, γ_{40}	0.380351	1.462798	(0.982,2.178)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Trimmed Conditional Model for Like Courses Using

Enrollment Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	14 October 2016, Friday
Time:	15:37:51

Specifications for this Bernoulli HLM2 run
Problem Title: PERSISTENCE 2ND MODEL LIKE ENROLL TIME MODEL TRIM

The data source for this run = PERSIST
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
$\qquad$ Level-1 Model
Prob($PERSIST_{ij}=1|\beta_j$) = ϕ_{ij}
$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ENROLLME_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(UPPER\_LO_{ij})$
$\qquad$ Level-2 Model
$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30}$

ENROLLME has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
$\qquad$ Mixed Model
$\eta_{ij} = \gamma_{00}$
$+ \gamma_{10}*ENROLLME_{ij}$
$+ \gamma_{20}*GENDER\_N_{ij}$
$+ \gamma_{30}*UPPER\_LO_{ij}$
$+ u_{0j} + u_{1j}*ENROLLME_{ij} + u_{2j}*GENDER\_N_{ij}$
Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 49)

τ

INTRCPT1,β_0	0.81368	-0.00148	-0.16317
ENROLLME,β_1	-0.00148	0.00002	-0.00208
GENDER_N,β_2	-0.16317	-0.00208	0.45206

τ (as correlations)

INTRCPT1,β_0	1.000	-0.403	-0.269
ENROLLME,β_1	-0.403	1.000	-0.763
GENDER_N,β_2	-0.269	-0.763	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.376
ENROLLME,β_1	0.182
GENDER_N,β_2	0.353

Note: The reliability estimates reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 2 = -1.871553E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.113206	0.285187	3.903	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.008707	0.001735	-5.018	19	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.139469	0.252968	0.551	19	0.588
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.776697	0.170556	4.554	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.113206	3.044101	(1.675,5.531)
For ENROLLME slope, β_1			
INTRCPT2, γ_{10}	-0.008707	0.991331	(0.988,0.995)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.139469	1.149663	(0.677,1.953)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.776697	2.174280	(1.556,3.038)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.113206	0.261862	4.251	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.008707	0.001543	-5.642	19	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.139469	0.241070	0.579	19	0.570
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.776697	0.200310	3.877	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval

For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.113206	3.044101	(1.759,5.267)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.008707	0.991331	(0.988,0.995)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.139469	1.149663	(0.694,1.905)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.776697	2.174280	(1.468,3.221)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	0.90204	0.81368	16	61.10740	<0.001
ENROLLME slope, u_1	0.00406	0.00002	16	43.00459	<0.001
GENDER_N slope, u_2	0.67235	0.45206	16	28.45026	0.028

Note: The chi-square statistics reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.690471E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	0.940744	0.261533	3.597	19	0.002
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.005310	0.001458	-3.641	19	0.002
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.050357	0.223944	0.225	19	0.824
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.622405	0.141088	4.411	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	0.940744	2.561886	(1.482,4.430)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.005310	0.994704	(0.992,0.998)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.050357	1.051646	(0.658,1.681)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.622405	1.863405	(1.413,2.458)	

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	0.940744	0.213893	4.398	19	<0.001
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	-0.005310	0.000931	-5.702	19	<0.001

For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.050357	0.180025	0.280	19	0.783
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.622405	0.149655	4.159	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	0.940744	2.561886	(1.637,4.009)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	-0.005310	0.994704	(0.993,0.997)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.050357	1.051646	(0.721,1.533)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.622405	1.863405	(1.389,2.499)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Initial Full Conditional Model for Like Courses Using Enrollment Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	18: 3:20

Specifications for this Bernoulli HLM2 run
Problem Title: PERSISTENCE INITIAL FULL MODEL LIKE USING ENROLL TIME

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
Level-1 Model
$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$
$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ENROLLME_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(UPPER\_LO_{ij})$
Level-2 Model
$\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$
$\beta_{1j} = \gamma_{10} + \gamma_{11}*(SATISFAC_j) + \gamma_{12}*(MODE_j) + u_{1j}$
$\beta_{2j} = \gamma_{20} + \gamma_{21}*(SATISFAC_j) + \gamma_{22}*(MODE_j) + u_{2j}$
$\beta_{3j} = \gamma_{30} + \gamma_{31}*(SATISFAC_j) + \gamma_{32}*(MODE_j)$

ENROLLME has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
Mixed Model
$\eta_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$
$+ \gamma_{10}*ENROLLME_{ij} + \gamma_{11}*SATISFAC_j*ENROLLME_{ij} + \gamma_{12}*MODE_j*ENROLLME_{ij}$
$+ \gamma_{20}*GENDER\_N_{ij} + \gamma_{21}*SATISFAC_j*GENDER\_N_{ij} + \gamma_{22}*MODE_j*GENDER\_N_{ij}$
$+ \gamma_{30}*UPPER\_LO_{ij} + \gamma_{31}*SATISFAC_j*UPPER\_LO_{ij} + \gamma_{32}*MODE_j*UPPER\_LO_{ij}$
$+ u_{0j} + u_{1j}*ENROLLME_{ij} + u_{2j}*GENDER\_N_{ij}$

Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 84)

τ

INTRCPT1,β_0	1.27587	-0.00307	-0.63745
ENROLLME,β_1	-0.00307	0.00001	0.00077
GENDER_N,β_2	-0.63745	0.00077	0.44338

τ (as correlations)

INTRCPT1,β_0	1.000	-0.776	-0.848
ENROLLME,β_1	-0.776	1.000	0.328
GENDER_N,β_2	-0.848	0.328	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.425
ENROLLME,β_1	0.151
GENDER_N,β_2	0.338

Note: The reliability estimates reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.
The value of the log-likelihood function at iteration 2 = -1.869748E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.303678	0.533546	4.318	17	<0.001
SATISFAC, γ_{01}	0.365424	1.590675	0.230	17	0.821
MODE, γ_{02}	-1.295414	0.630824	-2.054	17	0.056
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.001041	0.003720	0.280	17	0.783
SATISFAC, γ_{11}	0.001340	0.006896	0.194	17	0.848
MODE, γ_{12}	-0.012552	0.004023	-3.120	17	0.006
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.209788	0.387124	-0.542	17	0.595
SATISFAC, γ_{21}	1.202555	1.125069	1.069	17	0.300
MODE, γ_{22}	0.488793	0.441470	1.107	17	0.284
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.719620	0.269494	2.670	1270	0.008
SATISFAC, γ_{31}	-0.125841	0.714866	-0.176	1270	0.860
MODE, γ_{32}	0.095459	0.307696	0.310	1270	0.756

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.303678	10.010934	(3.248,30.860)	
SATISFAC, γ_{01}	0.365424	1.441125	(0.050,41.337)	
MODE, γ_{02}	-1.295414	0.273785	(0.072,1.036)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	0.001041	1.001041	(0.993,1.009)	
SATISFAC, γ_{11}	0.001340	1.001341	(0.987,1.016)	
MODE, γ_{12}	-0.012552	0.987526	(0.979,0.996)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.209788	0.810756	(0.358,1.835)	
SATISFAC, γ_{21}	1.202555	3.328609	(0.310,35.746)	
MODE, γ_{22}	0.488793	1.630348	(0.642,4.138)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.719620	2.053653	(1.210,3.485)	

SATISFAC, γ_{31}	-0.125841	0.881755	(0.217,3.585)
MODE, γ_{32}	0.095459	1.100164	(0.602,2.012)

<u>Final estimation of fixed effects</u>
<u>(Unit-specific model with robust standard errors)</u>

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.303678	0.434670	5.300	17	<0.001
SATISFAC, γ_{01}	0.365424	1.087520	0.336	17	0.741
MODE, γ_{02}	-1.295414	0.545144	-2.376	17	0.030
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.001041	0.004489	0.232	17	0.819
SATISFAC, γ_{11}	0.001340	0.004655	0.288	17	0.777
MODE, γ_{12}	-0.012552	0.004726	-2.656	17	0.017
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.209788	0.250751	-0.837	17	0.414
SATISFAC, γ_{21}	1.202555	0.827310	1.454	17	0.164
MODE, γ_{22}	0.488793	0.323989	1.509	17	0.150
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.719620	0.402762	1.787	1270	0.074
SATISFAC, γ_{31}	-0.125841	0.654140	-0.192	1270	0.847
MODE, γ_{32}	0.095459	0.448296	0.213	1270	0.831

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.303678	10.010934	(4.001,25.049)	
SATISFAC, γ_{01}	0.365424	1.441125	(0.145,14.298)	
MODE, γ_{02}	-1.295414	0.273785	(0.087,0.865)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	0.001041	1.001041	(0.992,1.011)	
SATISFAC, γ_{11}	0.001340	1.001341	(0.992,1.011)	
MODE, γ_{12}	-0.012552	0.987526	(0.978,0.997)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.209788	0.810756	(0.478,1.376)	
SATISFAC, γ_{21}	1.202555	3.328609	(0.581,19.071)	
MODE, γ_{22}	0.488793	1.630348	(0.823,3.230)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.719620	2.053653	(0.932,4.526)	
SATISFAC, γ_{31}	-0.125841	0.881755	(0.244,3.182)	
MODE, γ_{32}	0.095459	1.100164	(0.457,2.651)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

<u>Final estimation of variance components</u>

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.12955	1.27587	14	62.50538	<0.001
ENROLLME slope, u_1	0.00350	0.00001	14	41.82485	<0.001
GENDER_N slope, u_2	0.66587	0.44338	14	27.59369	0.016

Note: The chi-square statistics reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.746446E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.900715	0.497513	3.820	17	0.001
SATISFAC, γ_{01}	0.311405	1.462175	0.213	17	0.834
MODE, γ_{02}	-1.218461	0.596374	-2.043	17	0.057
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.002655	0.003582	0.741	17	0.469
SATISFAC, γ_{11}	0.001232	0.005994	0.205	17	0.840
MODE, γ_{12}	-0.011318	0.003825	-2.959	17	0.009
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.036694	0.326628	0.112	17	0.912
SATISFAC, γ_{21}	1.109200	1.000394	1.109	17	0.283
MODE, γ_{22}	0.387374	0.387739	0.999	17	0.332
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.628643	0.239509	2.625	1270	0.009
SATISFAC, γ_{31}	0.030489	0.642383	0.047	1270	0.962
MODE, γ_{32}	0.058752	0.278142	0.211	1270	0.833

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.900715	6.690675	(2.342,19.115)
SATISFAC, γ_{01}	0.311405	1.365342	(0.062,29.862)
MODE, γ_{02}	-1.218461	0.295685	(0.084,1.041)
For ENROLLME slope, β_1			
INTRCPT2, γ_{10}	0.002655	1.002659	(0.995,1.010)
SATISFAC, γ_{11}	0.001232	1.001232	(0.989,1.014)
MODE, γ_{12}	-0.011318	0.988745	(0.981,0.997)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.036694	1.037376	(0.521,2.067)
SATISFAC, γ_{21}	1.109200	3.031932	(0.367,25.029)
MODE, γ_{22}	0.387374	1.473107	(0.650,3.338)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.628643	1.875064	(1.172,3.000)
SATISFAC, γ_{31}	0.030489	1.030959	(0.292,3.636)
MODE, γ_{32}	0.058752	1.060513	(0.614,1.830)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.900715	0.302587	6.282	17	<0.001
SATISFAC, γ_{01}	0.311405	0.686701	0.453	17	0.656
MODE, γ_{02}	-1.218461	0.380020	-3.206	17	0.005
For ENROLLME slope, β_1					

INTRCPT2, γ_{10}	0.002655	0.004049	0.656	17	0.521
SATISFAC, γ_{11}	0.001232	0.002319	0.531	17	0.602
MODE, γ_{12}	-0.011318	0.004087	-2.769	17	0.013
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.036694	0.106462	0.345	17	0.735
SATISFAC, γ_{21}	1.109200	0.543075	2.042	17	0.057
MODE, γ_{22}	0.387374	0.192524	2.012	17	0.060
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.628643	0.333096	1.887	1270	0.059
SATISFAC, γ_{31}	0.030489	0.538780	0.057	1270	0.955
MODE, γ_{32}	0.058752	0.386272	0.152	1270	0.879

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.900715	6.690675	(3.533,12.669)	
SATISFAC, γ_{01}	0.311405	1.365342	(0.321,5.814)	
MODE, γ_{02}	-1.218461	0.295685	(0.133,0.659)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	0.002655	1.002659	(0.994,1.011)	
SATISFAC, γ_{11}	0.001232	1.001232	(0.996,1.006)	
MODE, γ_{12}	-0.011318	0.988745	(0.980,0.997)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.036694	1.037376	(0.829,1.299)	
SATISFAC, γ_{21}	1.109200	3.031932	(0.964,9.536)	
MODE, γ_{22}	0.387374	1.473107	(0.981,2.211)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.628643	1.875064	(0.975,3.604)	
SATISFAC, γ_{31}	0.030489	1.030959	(0.358,2.967)	
MODE, γ_{32}	0.058752	1.060513	(0.497,2.263)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Trimmed Full Conditional Model for Like Courses Using

Enrollment Time

Specifications for this Bernoulli HLM2 run
Problem Title: PERSISTENCE FULL MODEL TRIMMED LIKE USING ENROLL TIME

The data source for this run = like
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
  Level-1 Model
  $\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$
  $\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
  $\eta_{ij} = \beta_{0j} + \beta_{1j}*(ENROLLME_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(UPPER\_LO_{ij})$
  Level-2 Model
  $\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$
  $\beta_{1j} = \gamma_{10} + \gamma_{11}*(MODE_j) + u_{1j}$
  $\beta_{2j} = \gamma_{20} + u_{2j}$
  $\beta_{3j} = \gamma_{30}$

ENROLLME has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
  Mixed Model
  $\eta_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$
  $+ \gamma_{10}*ENROLLME_{ij} + \gamma_{11}*MODE_j*ENROLLME_{ij}$
  $+ \gamma_{20}*GENDER\_N_{ij}$
  $+ \gamma_{30}*UPPER\_LO_{ij}$
  $+ u_{0j} + u_{1j}*ENROLLME_{ij} + u_{2j}*GENDER\_N_{ij}$
Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 629)

τ

INTRCPT1,β_0	1.08028	-0.00223	-0.54360
ENROLLME,β_1	-0.00223	0.00001	-0.00011
GENDER_N,β_2	-0.54360	-0.00011	0.52137

τ (as correlations)

INTRCPT1,β_0	1.000	-0.654	-0.724
ENROLLME,β_1	-0.654	1.000	-0.046
GENDER_N,β_2	-0.724	-0.046	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.405
ENROLLME,β_1	0.138
GENDER_N,β_2	0.367

Note: The reliability estimates reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

The value of the log-likelihood function at iteration 2 = -1.871359E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.080474	0.470157	4.425	17	<0.001
SATISFAC, γ_{01}	1.472689	0.704529	2.090	17	0.052
MODE, γ_{02}	-0.952921	0.489614	-1.946	17	0.068
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.001996	0.003704	0.539	18	0.597
MODE, γ_{11}	-0.013129	0.003930	-3.341	18	0.004
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.145850	0.265731	0.549	19	0.589
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.775870	0.170337	4.555	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.080474	8.008262	(2.970,21.596)	
SATISFAC, γ_{01}	1.472689	4.360948	(0.986,19.283)	
MODE, γ_{02}	-0.952921	0.385613	(0.137,1.083)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	0.001996	1.001998	(0.994,1.010)	
MODE, γ_{11}	-0.013129	0.986957	(0.979,0.995)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.145850	1.157022	(0.663,2.018)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.775870	2.172480	(1.555,3.035)	

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.080474	0.455563	4.567	17	<0.001
SATISFAC, γ_{01}	1.472689	0.428044	3.441	17	0.003
MODE, γ_{02}	-0.952921	0.489308	-1.947	17	0.068

For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.001996	0.004537	0.440	18	0.665
MODE, γ_{11}	-0.013129	0.004644	-2.827	18	0.011
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.145850	0.237777	0.613	19	0.547
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.775870	0.187488	4.138	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	2.080474	8.008262	(3.063,20.941)
SATISFAC, γ_{01}	1.472689	4.360948	(1.767,10.760)
MODE, γ_{02}	-0.952921	0.385613	(0.137,1.083)
For ENROLLME slope, β_1			
INTRCPT2, γ_{10}	0.001996	1.001998	(0.992,1.012)
MODE, γ_{11}	-0.013129	0.986957	(0.977,0.997)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.145850	1.157022	(0.703,1.904)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.775870	2.172480	(1.504,3.138)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.03936	1.08028	14	62.06507	<0.001
ENROLLME slope, u_1	0.00328	0.00001	15	41.49368	<0.001
GENDER_N slope, u_2	0.72206	0.52137	16	28.86530	0.025

Note: The chi-square statistics reported above are based on only 17 of 20 units that had sufficient data for computation. Fixed effects and variance components are based on all the data.

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.741260E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.781023	0.444852	4.004	17	<0.001
SATISFAC, γ_{01}	1.421805	0.672458	2.114	17	0.050
MODE, γ_{02}	-0.955641	0.467049	-2.046	17	0.057
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.003200	0.003594	0.890	18	0.385
MODE, γ_{11}	-0.011537	0.003756	-3.072	18	0.007
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.239858	0.235765	1.017	19	0.322
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.670659	0.148086	4.529	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			

INTRCPT2, γ_{00}	1.781023	5.935926	(2.322,15.175)
SATISFAC, γ_{01}	1.421805	4.144595	(1.003,17.128)
MODE, γ_{02}	-0.955641	0.384565	(0.144,1.030)
For ENROLLME slope, β_1			
INTRCPT2, γ_{10}	0.003200	1.003205	(0.996,1.011)
MODE, γ_{11}	-0.011537	0.988529	(0.981,0.996)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.239858	1.271068	(0.776,2.082)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.670659	1.955525	(1.462,2.615)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.781023	0.375916	4.738	17	<0.001
SATISFAC, γ_{01}	1.421805	0.403729	3.522	17	0.003
MODE, γ_{02}	-0.955641	0.407763	-2.344	17	0.032
For ENROLLME slope, β_1					
INTRCPT2, γ_{10}	0.003200	0.004122	0.776	18	0.448
MODE, γ_{11}	-0.011537	0.004078	-2.829	18	0.011
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.239858	0.164909	1.454	19	0.162
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.670659	0.148109	4.528	1272	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.781023	5.935926	(2.685,13.121)	
SATISFAC, γ_{01}	1.421805	4.144595	(1.768,9.715)	
MODE, γ_{02}	-0.955641	0.384565	(0.163,0.909)	
For ENROLLME slope, β_1				
INTRCPT2, γ_{10}	0.003200	1.003205	(0.995,1.012)	
MODE, γ_{11}	-0.011537	0.988529	(0.980,0.997)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.239858	1.271068	(0.900,1.795)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.670659	1.955525	(1.462,2.615)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Initial Conditional Model for Like Courses Using Active

Completion Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	14 October 2016, Friday
Time:	15:47:59

Specifications for this Bernoulli HLM2 run
Problem Title: PERSIST LIKE COURSES USING ACTIVE 2ND MODEL

The data source for this run = PERSIST
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
$\quad$ <u>Level-1 Model</u>
$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$
$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(PRIORSP_{ij}) + \beta_{4j}*(UPPER\_LO_{ij})$
$\quad$ <u>Level-2 Model</u>
$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10} + u_{1j}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30} + u_{3j}$
$\beta_{4j} = \gamma_{40} + u_{4j}$

ACTIVE_C has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
$\quad$ <u>Mixed Model</u>
$\eta_{ij} = \gamma_{00}$
$+ \gamma_{10}*ACTIVE\_C_{ij}$
$+ \gamma_{20}*GENDER\_N_{ij}$

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$$+ \gamma_{30}*PRIORSP_{ij}$$
$$+ \gamma_{40}*UPPER\_LO_{ij}$$
$$+ u_{0j} + u_{1j}*ACTIVE\_C_{ij} + u_{2j}*GENDER\_N_{ij} + u_{3j}*PRIORSP_{ij}$$
$$+ u_{4j}*UPPER\_LO_{ij}$$

Run-time deletion has reduced the number of level-1 records to 1231

Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 3867)

τ

INTRCPT1,β_0	2.93209	-0.00004	-1.34445	0.28317	-0.39207
ACTIVE_C,β_1	-0.00004	0.00000	0.00091	0.00042	-0.00032
GENDER_N,β_2	-1.34445	0.00091	0.80963	-0.03695	0.10592
PRIORSP,β_3	0.28317	0.00042	-0.03695	0.08707	-0.15860
UPPER_LO,β_4	-0.39207	-0.00032	0.10592	-0.15860	0.57041

τ (as correlations)

INTRCPT1,β_0	1.000	-0.013	-0.873	0.560	-0.303
ACTIVE_C,β_1	-0.013	1.000	0.499	0.703	-0.208
GENDER_N,β_2	-0.873	0.499	1.000	-0.139	0.156
PRIORSP,β_3	0.560	0.703	-0.139	1.000	-0.712
UPPER_LO,β_4	-0.303	-0.208	0.156	-0.712	1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.437
ACTIVE_C,β_1	0.070
GENDER_N,β_2	0.332
PRIORSP,β_3	0.076
UPPER_LO,β_4	0.259

The value of the log-likelihood function at iteration 2 = -1.653027E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.056589	0.482604	4.261	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003472	0.001611	2.154	19	0.044
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.137860	0.321773	-0.428	19	0.673
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	-0.082619	0.228416	-0.362	19	0.722
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.717384	0.316919	2.264	19	0.035

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.056589	7.819249	(2.846,21.481)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.003472	1.003478	(1.000,1.007)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.137860	0.871221	(0.444,1.709)	
For PRIORSP slope, β_3				
INTRCPT2, γ_{30}	-0.082619	0.920701	(0.571,1.485)	
For UPPER_LO slope, β_4				

	INTRCPT2, γ_{40}	0.717384	2.049066	(1.055,3.979)	

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.056589	0.462214	4.449	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003472	0.001250	2.778	19	0.012
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.137860	0.301747	-0.457	19	0.653
For PRIORSP slope, β_3					
INTRCPT2, γ_{30}	-0.082619	0.160224	-0.516	19	0.612
For UPPER_LO slope, β_4					
INTRCPT2, γ_{40}	0.717384	0.303311	2.365	19	0.029

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.056589	7.819249	(2.970,20.583)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.003472	1.003478	(1.001,1.006)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.137860	0.871221	(0.463,1.639)	
For PRIORSP slope, β_3				
INTRCPT2, γ_{30}	-0.082619	0.920701	(0.658,1.288)	
For UPPER_LO slope, β_4				
INTRCPT2, γ_{40}	0.717384	2.049066	(1.086,3.867)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.71234	2.93209	19	62.74597	<0.001
ACTIVE_C slope, u_1	0.00203	0.00000	19	24.83319	0.166
GENDER_N slope, u_2	0.89979	0.80963	19	35.50432	0.012
PRIORSP slope, u_3	0.29507	0.08707	19	11.41698	>0.500
UPPER_LO slope, u_4	0.75526	0.57041	19	25.72479	0.138

Persistence Bernouilli Trimmed Conditional Model for Like Courses Using Active Completion Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	14 October 2016, Friday
Time:	15:54:27

Problem Title: PERSIST LIKE COURSES USING ACTIVE 2ND MODEL TRIM

The data source for this run = PERSIST
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST

Summary of the model specified

Level-1 Model

$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$

$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$

$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(UPPER\_LO_{ij})$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$

$\beta_{1j} = \gamma_{10}$

$\beta_{2j} = \gamma_{20} + u_{2j}$

$\beta_{3j} = \gamma_{30}$

ACTIVE_C has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$

Mixed Model

$\eta_{ij} = \gamma_{00}$
$+ \gamma_{10}*ACTIVE\_C_{ij}$
$+ \gamma_{20}*GENDER\_N_{ij}$
$+ \gamma_{30}*UPPER\_LO_{ij}$
$+ u_{0j} + u_{2j}*GENDER\_N_{ij}$

Run-time deletion has reduced the number of level-1 records to 1231

τ

INTRCPT1,β_0 3.01223   -1.28424
GENDER_N,β_2 -1.28424   0.79874

τ (as correlations)
INTRCPT1,β_0 1.000 -0.828
GENDER_N,β_2 -0.828   1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.677
GENDER_N,β_2	0.355

The value of the log-likelihood function at iteration 2 = -1.664106E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.917708	0.473039	4.054	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003861	0.001444	2.674	1189	0.008
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.066797	0.322621	-0.207	19	0.838
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.785369	0.204686	3.837	1189	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.917708	6.805344	(2.527,18.325)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.003861	1.003869	(1.001,1.007)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.066797	0.935385	(0.476,1.838)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.785369	2.193216	(1.468,3.277)	

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.917708	0.466754	4.109	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003861	0.001295	2.981	1189	0.003
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.066797	0.310970	-0.215	19	0.832
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.785369	0.230261	3.411	1189	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	1.917708	6.805344	(2.561,18.085)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.003861	1.003869	(1.001,1.006)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.066797	0.935385	(0.488,1.794)	

	For UPPER_LO slope, β_3		
INTRCPT2, γ_{30}	0.785369	2.193216	(1.396,3.446)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.73558	3.01223	19	90.44560	<0.001
GENDER_N slope, u_2	0.89372	0.79874	19	34.36288	0.017

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.570450E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.288853	0.431192	2.989	19	0.008
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003580	0.001304	2.745	1189	0.006
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.283359	0.272537	1.040	19	0.312
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.642597	0.165807	3.876	1189	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.288853	3.628623	(1.471,8.951)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.003580	1.003587	(1.001,1.006)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.283359	1.327581	(0.750,2.349)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.642597	1.901412	(1.373,2.632)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	1.288853	0.269673	4.779	19	<0.001
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.003580	0.001061	3.375	1189	<0.001
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.283359	0.176807	1.603	19	0.126
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.642597	0.161555	3.978	1189	<0.001

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	1.288853	3.628623	(2.063,6.382)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.003580	1.003587	(1.002,1.006)

For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.283359	1.327581	(0.917,1.922)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.642597	1.901412	(1.385,2.611)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Initial Full Conditional Model for Like Courses Using Active Completion Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	17:42:50

Problem Title: PERSISTENCE INITIAL FULL MODEL LIKE COURSES USING ACTIVE TIME

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST

Summary of the model specified

Level-1 Model

$$\text{Prob}(PERSIST_{ij}=1|\beta_j) = \phi_{ij}$$
$$\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$$
$$\eta_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij}) + \beta_{2j}*(GENDER\_N_{ij}) + \beta_{3j}*(UPPER\_LO_{ij})$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + \gamma_{11}*(SATISFAC_j) + \gamma_{12}*(MODE_j)$$
$$\beta_{2j} = \gamma_{20} + \gamma_{21}*(SATISFAC_j) + \gamma_{22}*(MODE_j) + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + \gamma_{31}*(SATISFAC_j) + \gamma_{32}*(MODE_j)$$

ACTIVE_C has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$

Mixed Model

$$\eta_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$$
$$+ \gamma_{10}*ACTIVE\_C_{ij} + \gamma_{11}*SATISFAC_j*ACTIVE\_C_{ij} + \gamma_{12}*MODE_j*ACTIVE\_C_{ij}$$
$$+ \gamma_{20}*GENDER\_N_{ij} + \gamma_{21}*SATISFAC_j*GENDER\_N_{ij} + \gamma_{22}*MODE_j*GENDER\_N_{ij}$$
$$+ \gamma_{30}*UPPER\_LO_{ij} + \gamma_{31}*SATISFAC_j*UPPER\_LO_{ij} + \gamma_{32}*MODE_j*UPPER\_LO_{ij}$$
$$+ u_{0j} + u_{2j}*GENDER\_N_{ij}$$

Run-time deletion has reduced the number of level-1 records to 1231

τ

INTRCPT1,β_0 3.00259   -1.29042
GENDER_N,β_2 -1.29042   0.67097

τ (as correlations)
INTRCPT1,β_0 1.000 -0.909
GENDER_N,β_2 -0.909   1.000

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.663
GENDER_N,β_2	0.320

The value of the log-likelihood function at iteration 2 = -1.680100E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.038412	0.754164	4.029	17	<0.001
SATISFAC, γ_{01}	-0.572431	2.305891	-0.248	17	0.807
MODE, γ_{02}	-1.633894	0.901697	-1.812	17	0.088
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.011825	0.005509	2.147	1185	0.032
SATISFAC, γ_{11}	0.009189	0.005691	1.615	1185	0.107
MODE, γ_{12}	-0.009387	0.005670	-1.655	1185	0.098
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.357497	0.482942	-0.740	17	0.469
SATISFAC, γ_{21}	1.838673	1.356270	1.356	17	0.193
MODE, γ_{22}	0.424157	0.560415	0.757	17	0.459
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.671078	0.361562	1.856	1185	0.064
SATISFAC, γ_{31}	-0.523086	0.846063	-0.618	1185	0.537
MODE, γ_{32}	0.213009	0.409769	0.520	1185	0.603

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	3.038412	20.872076	(4.251,102.483)	
SATISFAC, γ_{01}	-0.572431	0.564152	(0.004,73.186)	
MODE, γ_{02}	-1.633894	0.195168	(0.029,1.308)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.011825	1.011895	(1.001,1.023)	
SATISFAC, γ_{11}	0.009189	1.009232	(0.998,1.021)	
MODE, γ_{12}	-0.009387	0.990657	(0.980,1.002)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	-0.357497	0.699425	(0.252,1.938)	
SATISFAC, γ_{21}	1.838673	6.288189	(0.359,109.992)	
MODE, γ_{22}	0.424157	1.528302	(0.468,4.986)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.671078	1.956344	(0.962,3.977)	
SATISFAC, γ_{31}	-0.523086	0.592689	(0.113,3.117)	
MODE, γ_{32}	0.213009	1.237395	(0.554,2.765)	

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.038412	0.822973	3.692	17	0.002
SATISFAC, γ_{01}	-0.572431	1.743496	-0.328	17	0.747
MODE, γ_{02}	-1.633894	1.004150	-1.627	17	0.122
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.011825	0.012048	0.982	1185	0.327
SATISFAC, γ_{11}	0.009189	0.002917	3.150	1185	0.002
MODE, γ_{12}	-0.009387	0.012047	-0.779	1185	0.436
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	-0.357497	0.236574	-1.511	17	0.149
SATISFAC, γ_{21}	1.838673	0.978274	1.880	17	0.077
MODE, γ_{22}	0.424157	0.393309	1.078	17	0.296
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.671078	0.543751	1.234	1185	0.217
SATISFAC, γ_{31}	-0.523086	0.817583	-0.640	1185	0.522
MODE, γ_{32}	0.213009	0.616822	0.345	1185	0.730

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	3.038412	20.872076	(3.676,118.497)
SATISFAC, γ_{01}	-0.572431	0.564152	(0.014,22.339)
MODE, γ_{02}	-1.633894	0.195168	(0.023,1.624)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.011825	1.011895	(0.988,1.036)
SATISFAC, γ_{11}	0.009189	1.009232	(1.003,1.015)
MODE, γ_{12}	-0.009387	0.990657	(0.968,1.014)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	-0.357497	0.699425	(0.425,1.152)
SATISFAC, γ_{21}	1.838673	6.288189	(0.798,49.543)
MODE, γ_{22}	0.424157	1.528302	(0.666,3.504)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.671078	1.956344	(0.673,5.685)
SATISFAC, γ_{31}	-0.523086	0.592689	(0.119,2.948)
MODE, γ_{32}	0.213009	1.237395	(0.369,4.150)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.73280	3.00259	17	68.26801	<0.001
GENDER_N slope, u_2	0.81913	0.67097	17	24.50117	0.106

Results for Population-Average Model
The value of the log-likelihood function at iteration 2 = -1.566737E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
INTRCPT2, γ_{00}	2.228587	0.647252	3.443	17	0.003
SATISFAC, γ_{01}	-0.477155	2.093390	-0.228	17	0.822
MODE, γ_{02}	-1.365923	0.799037	-1.709	17	0.106
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.009320	0.004057	2.297	1185	0.022
SATISFAC, γ_{11}	0.008288	0.005189	1.597	1185	0.110
MODE, γ_{12}	-0.006958	0.004256	-1.635	1185	0.102
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.087815	0.388967	0.226	17	0.824
SATISFAC, γ_{21}	1.531313	1.175781	1.302	17	0.210
MODE, γ_{22}	0.327555	0.468927	0.699	17	0.494
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.539899	0.296479	1.821	1185	0.069
SATISFAC, γ_{31}	-0.344015	0.737398	-0.467	1185	0.641
MODE, γ_{32}	0.190567	0.344681	0.553	1185	0.580

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	2.228587	9.286730	(2.370,36.390)
SATISFAC, γ_{01}	-0.477155	0.620546	(0.007,51.413)
MODE, γ_{02}	-1.365923	0.255145	(0.047,1.377)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.009320	1.009363	(1.001,1.017)
SATISFAC, γ_{11}	0.008288	1.008323	(0.998,1.019)
MODE, γ_{12}	-0.006958	0.993066	(0.985,1.001)
For GENDER_N slope, β_2			
INTRCPT2, γ_{20}	0.087815	1.091786	(0.481,2.481)
SATISFAC, γ_{21}	1.531313	4.624245	(0.387,55.269)
MODE, γ_{22}	0.327555	1.387572	(0.516,3.732)
For UPPER_LO slope, β_3			
INTRCPT2, γ_{30}	0.539899	1.715834	(0.959,3.070)
SATISFAC, γ_{31}	-0.344015	0.708918	(0.167,3.012)
MODE, γ_{32}	0.190567	1.209936	(0.615,2.379)

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.228587	0.373461	5.967	17	<0.001
SATISFAC, γ_{01}	-0.477155	0.798357	-0.598	17	0.558
MODE, γ_{02}	-1.365923	0.499696	-2.734	17	0.014
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.009320	0.006083	1.532	1185	0.126
SATISFAC, γ_{11}	0.008288	0.002517	3.293	1185	0.001
MODE, γ_{12}	-0.006958	0.006135	-1.134	1185	0.257
For GENDER_N slope, β_2					
INTRCPT2, γ_{20}	0.087815	0.075820	1.158	17	0.263
SATISFAC, γ_{21}	1.531313	0.464861	3.294	17	0.004
MODE, γ_{22}	0.327555	0.193825	1.690	17	0.109
For UPPER_LO slope, β_3					
INTRCPT2, γ_{30}	0.539899	0.371844	1.452	1185	0.147
SATISFAC, γ_{31}	-0.344015	0.584553	-0.589	1185	0.556

MODE, γ_{32}	0.190567	0.441510	0.432	1185	0.666

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.228587	9.286730	(4.223,20.422)	
SATISFAC, γ_{01}	-0.477155	0.620546	(0.115,3.345)	
MODE, γ_{02}	-1.365923	0.255145	(0.089,0.732)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.009320	1.009363	(0.997,1.021)	
SATISFAC, γ_{11}	0.008288	1.008323	(1.003,1.013)	
MODE, γ_{12}	-0.006958	0.993066	(0.981,1.005)	
For GENDER_N slope, β_2				
INTRCPT2, γ_{20}	0.087815	1.091786	(0.930,1.281)	
SATISFAC, γ_{21}	1.531313	4.624245	(1.734,12.332)	
MODE, γ_{22}	0.327555	1.387572	(0.922,2.089)	
For UPPER_LO slope, β_3				
INTRCPT2, γ_{30}	0.539899	1.715834	(0.827,3.559)	
SATISFAC, γ_{31}	-0.344015	0.708918	(0.225,2.232)	
MODE, γ_{32}	0.190567	1.209936	(0.509,2.877)	

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Persistence Bernouilli Trimmed Full Conditional Model for Like Courses Using

Active Completion Time

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com
	www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	28 October 2016, Friday
Time:	17:45:52

Specifications for this Bernoulli HLM2 run
Problem Title: PERSISTENCE FULL MODEL TRIMMED LIKE COURSES USING ACTIVE TIME

The data source for this run = LIKE
The command file for this run = C:\Users\nagelt\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\nagelt\Desktop\hlm2.html
The maximum number of level-1 units = 1333
The maximum number of level-2 units = 20
The maximum number of micro iterations = 14

Method of estimation: restricted PQL
Maximum number of macro iterations = 100

Distribution at Level-1: Bernoulli

The outcome variable is PERSIST
Summary of the model specified
       Level-1 Model
  Prob($PERSIST_{ij}=1|\beta_j$) = ϕ_{ij}
  $\log[\phi_{ij}/(1 - \phi_{ij})] = \eta_{ij}$
  $\eta_{ij} = \beta_{0j} + \beta_{1j}*(ACTIVE\_C_{ij})$
       Level-2 Model
  $\beta_{0j} = \gamma_{00} + \gamma_{01}*(SATISFAC_j) + \gamma_{02}*(MODE_j) + u_{0j}$
  $\beta_{1j} = \gamma_{10} + \gamma_{11}*(SATISFAC_j) + \gamma_{12}*(MODE_j)$

ACTIVE_C has been centered around the grand mean.

Level-1 variance = $1/[\phi_{ij}(1-\phi_{ij})]$
       Mixed Model
  $\eta_{ij} = \gamma_{00} + \gamma_{01}*SATISFAC_j + \gamma_{02}*MODE_j$
  $+ \gamma_{10}*ACTIVE\_C_{ij} + \gamma_{11}*SATISFAC_j*ACTIVE\_C_{ij} + \gamma_{12}*MODE_j*ACTIVE\_C_{ij}$
  $+ u_{0j}$

Run-time deletion has reduced the number of level-1 records to 1231

The value of the log-likelihood function at iteration 11 = -4.138317E+002
Results for Non-linear Model with the Logit Link Function
Unit-Specific Model, PQL Estimation - (macro iteration 10)

τ
 INTRCPT1,β_0 1.34669

Random level-1 coefficient	Reliability estimate
INTRCPT1, β_0	0.763

The value of the log-likelihood function at iteration 2 = -1.701862E+003

Final estimation of fixed effects: (Unit-specific model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.121854	0.509891	6.123	17	<0.001
SATISFAC, γ_{01}	0.521085	1.439746	0.362	17	0.722
MODE, γ_{02}	-1.167001	0.605434	-1.928	17	0.071
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.010511	0.005308	1.980	1208	0.048
SATISFAC, γ_{11}	0.009191	0.005555	1.654	1208	0.098
MODE, γ_{12}	-0.008614	0.005469	-1.575	1208	0.116

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	3.121854	22.688399	(7.737,66.535)
SATISFAC, γ_{01}	0.521085	1.683853	(0.081,35.126)
MODE, γ_{02}	-1.167001	0.311299	(0.087,1.117)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.010511	1.010566	(1.000,1.021)
SATISFAC, γ_{11}	0.009191	1.009233	(0.998,1.020)
MODE, γ_{12}	-0.008614	0.991423	(0.981,1.002)

Final estimation of fixed effects
(Unit-specific model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	3.121854	0.725004	4.306	17	<0.001
SATISFAC, γ_{01}	0.521085	1.186087	0.439	17	0.666
MODE, γ_{02}	-1.167001	0.819933	-1.423	17	0.173
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.010511	0.011046	0.952	1208	0.342
SATISFAC, γ_{11}	0.009191	0.003461	2.655	1208	0.008
MODE, γ_{12}	-0.008614	0.011065	-0.779	1208	0.436

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval
For INTRCPT1, β_0			
INTRCPT2, γ_{00}	3.121854	22.688399	(4.914,104.754)
SATISFAC, γ_{01}	0.521085	1.683853	(0.138,20.568)
MODE, γ_{02}	-1.167001	0.311299	(0.055,1.756)
For ACTIVE_C slope, β_1			
INTRCPT2, γ_{10}	0.010511	1.010566	(0.989,1.033)
SATISFAC, γ_{11}	0.009191	1.009233	(1.002,1.016)
MODE, γ_{12}	-0.008614	0.991423	(0.970,1.013)

The robust standard errors are appropriate for datasets having a moderate to large number of level 2 units. These data do not meet this criterion.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	d.f.	χ^2	p-value
INTRCPT1, u_0	1.16047	1.34669	17	88.53370	<0.001

Results for Population-Average Model

The value of the log-likelihood function at iteration 2 = -1.704215E+003

Final estimation of fixed effects: (Population-average model)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.826953	0.482835	5.855	17	<0.001
SATISFAC, γ_{01}	0.420111	1.359556	0.309	17	0.761
MODE, γ_{02}	-1.165873	0.580243	-2.009	17	0.061
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.010245	0.005432	1.886	1208	0.060
SATISFAC, γ_{11}	0.009123	0.005592	1.632	1208	0.103
MODE, γ_{12}	-0.008259	0.005592	-1.477	1208	0.140

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.826953	16.893914	(6.099,46.793)	
SATISFAC, γ_{01}	0.420111	1.522130	(0.086,26.810)	
MODE, γ_{02}	-1.165873	0.311650	(0.092,1.060)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.010245	1.010297	(1.000,1.021)	
SATISFAC, γ_{11}	0.009123	1.009165	(0.998,1.020)	
MODE, γ_{12}	-0.008259	0.991775	(0.981,1.003)	

Final estimation of fixed effects
(Population-average model with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. d.f.	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	2.826953	0.615491	4.593	17	<0.001
SATISFAC, γ_{01}	0.420111	0.754135	0.557	17	0.585
MODE, γ_{02}	-1.165873	0.687982	-1.695	17	0.108
For ACTIVE_C slope, β_1					
INTRCPT2, γ_{10}	0.010245	0.011010	0.931	1208	0.352
SATISFAC, γ_{11}	0.009123	0.003586	2.544	1208	0.011
MODE, γ_{12}	-0.008259	0.011030	-0.749	1208	0.454

Fixed Effect	Coefficient	Odds Ratio	Confidence Interval	
For INTRCPT1, β_0				
INTRCPT2, γ_{00}	2.826953	16.893914	(4.610,61.907)	
SATISFAC, γ_{01}	0.420111	1.522130	(0.310,7.473)	
MODE, γ_{02}	-1.165873	0.311650	(0.073,1.331)	
For ACTIVE_C slope, β_1				
INTRCPT2, γ_{10}	0.010245	1.010297	(0.989,1.032)	
SATISFAC, γ_{11}	0.009123	1.009165	(1.002,1.016)	
MODE, γ_{12}	-0.008259	0.991775	(0.971,1.013)	

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