COURSE FORMAT MATTERS: EFFECTS ON STUDENT RETENTION AND ACADEMIC PERFORMANCE IN TWO-YEAR POSTSECONDARY INSTITUTIONS

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Dedication

To Jesus and all those who have supported me when I faltered

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Abstract

Retention rates are considerably lower for students attending two-year postsecondary institutions when compared to their counterparts at four-year postsecondary institutions. This disparity may stem from the greater number of nontraditional students at two-year postsecondary institutions, who often struggle to balance their studies and non-academic responsibilities. In order to enhance the academic performance and persistence of students at two-year postsecondary institutions, educators have offered course formats that are more flexible than the traditional face-to-face format. This study compared student retention and academic performance across the following three course formats: traditional (16-week face-to-face), online (16-week online), and online compressed (5-week online). This study also investigated if the effects of six student and course characteristics (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM) varied across the different course formats in terms of student retention and academic performance. Multilevel modeling was used to analyze the persistence and academic performance of 22,280 students attending seven community colleges in Hawai‘i. Results demonstrated that the 5-week online course format yielded higher academic performance than the traditional course format. However, there was no significant difference between the 16-week online and traditional course formats in terms of academic performance. For student retention, the 5-week online course format produced the highest retention rates, followed by the traditional course format with the 16-week online course format producing the lowest retention rates. Overall, the effects of the six characteristics on student outcomes varied across the different course formats. This study concluded that 5-week online courses had the potential to enhance student retention and academic performance at two-year postsecondary institutions.

Keywords: student retention, academic performance, online compressed courses, flexibility, multilevel modeling of categorical outcomes, community colleges, nontraditional students

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Chapter 1: Introduction

Retention rates have been considerably lower for students attending two-year postsecondary institutions when compared to their counterparts at four-year postsecondary institutions (National Center for Education Statistics, 2021a). From 2006 to 2020, annual retention rates for students at two-year institutions were approximately 20 percent lower than students at four-year institutions. Among the many factors that can explain this substantial gap, the proportion of nontraditional students at each institution has been widely considered to be one of the most influential factors (Fike & Fike, 2008; Juszkiewicz, 2017). Compared to traditional students, nontraditional students are at a higher risk of dropping out (National Audit Office, 2007; Provasnik & Planty, 2008). The U.S. Department of Education defined nontraditional students as those who have one or more of the following characteristics: (a) are part-time students, (b) work full time, (c) are financially independent, (d) do not attend college in the same year that they graduate from high school, (e) do not have a high school diploma, and (f) are parents (Gilardi & Guglielmetti, 2011).

The National Center for Education Statistics (2013) reported the percentages of undergraduate students with the aforementioned nontraditional characteristics at public two-year and four-year institutions from 2011 to 2012. Each of these characteristics was more than twice as prevalent at public two-year institutions when compared to public four-year institutions. For example, about 20% of undergraduate students at public four-year institutions worked full time while over 45% of undergraduate students at public two-year institutions worked full time. Also, only 19.7% of undergraduate students at public four-year institutions were financially independent while 44.4% of undergraduate students at public two-year institutions were financially independent. Disparities between two-year and four-year institutions have continued for the past decade. For example, in fall 2020, 27% of undergraduate students at four-year institutions were enrolled part time while 63% of undergraduate students at two-year institutions were enrolled part time (National Center for Education Statistics, 2022).

Many studies showed that the characteristics of nontraditional students negatively impacted academic performance and student retention (Applegate & Daly, 2006; Darolia, 2013; Fike & Fike, 2008; García-Vargas et al., 2016; Juszkiewicz, 2017). For example, García-Vargas et al. (2016) studied the influence of work hours on student academic performance within the context of higher education. They found that work hours negatively affected the academic performance of undergraduate students. Negative effects were far more pronounced for students who worked more. Similarly, Applegate and Daly (2006) found that working more than 22 hours per week had a negative influence on undergraduate students' academic performance. The National Center for Education Statistics (2020) reported that from 2000 to 2018, the percentage of nontraditional students who worked 20 or more hours per week was more than double that of traditional students who also worked 20 or more hours per week.

The characteristics of nontraditional students also negatively affected student retention. Fike and Fike (2008) studied how the number of credits earned affected the persistence of first-time college students at a community college in Texas. The number of credits earned is an important point of consideration, given that nontraditional students typically earn credits at slower rates than traditional students (McFarland et al., 2019). Fike and Fike found that the number of credits that students earned in their first semester positively affected their persistence from the first semester through the second semester and from the first semester through the fourth semester. Summer semesters were not included in their study.

Furthermore, the American Association of Community Colleges tracked two groups of first-time college students at two-year institutions from fall 2010 to fall 2016 (Juszkiewicz, 2017). One group was enrolled on a full-time basis, and the other group was enrolled on a part-time basis. The results showed that by the end of fall 2016, about 55% of the full-time students graduated while only 20.4% of the part-time students graduated. Additionally, many studies showed a negative relationship between delayed entry into higher education and degree completion (Goldrick-Rab & Han, 2011; Roksa & Velez, 2012; Rowan-Kenyon, 2007).

Therefore, two-year postsecondary institutions should take into account the main characteristics of nontraditional students when they explore ways to increase student retention and academic performance. One way to achieve this increase is to utilize course formats that provide students with greater flexibility regarding when, where, and how they learn, compared to traditional courses, which are delivered face to face over 14 to 16 weeks. Nontraditional students valued the flexibility offered by course formats to a significantly greater extent than traditional students (Crews & Butterfield, 2014). Nontraditional students reported that the flexibility offered by course formats permitted them to work and study at the same time. They also reported that increased flexibility enabled them to study where and when they wanted. Crews and Butterfield (2014) concluded that flexibility is particularly important for nontraditional students who have more demanding schedules outside of academia. The following section describes the major elements of flexibility and then examines the flexibility offered by different course formats: traditional, online, face-to-face compressed, and online compressed.

Conceptual Framework

Major Elements of Flexibility

Andrade and Alden-Rivers (2019) identified three major elements of flexibility within the context of learning and teaching: place, mode, and pace. Place refers to the location at which learning takes place. Applying the idea of place at the course level, learning can occur in a variety of places, such as a classroom or a personal residence. Mode refers to the extent to which technology is used to deliver course content. Lastly, pace refers to how intensively a course is scheduled. For example, a course with accelerated pacing compresses the content of a traditional 14- to 16-week course into a shorter time frame. Pace also refers to when students can access course materials (Chizmar & Walbert, 1999). For example, the option to watch recorded lectures at convenient times or pause a lecture to take more detailed notes provides greater pacing flexibility.

The three elements of flexible learning (i.e., place, mode, and pace) can be depicted as the length, height, and depth of a three-dimensional space. In this space, the three dimensions emanate from a single corner. Various course formats can be positioned at different locations within this space depending on the amount of flexibility that the formats offer. A course format positioned closest to the corner provides the least amount of flexibility in terms of place, mode, and pace. As the location of a course format moves farther away from the corner, the flexibility of the course format increases. For example, if a course format moves farther away from the corner along the length dimension, flexibility in terms of place increases. Next, I analyze the flexibility offered by different course formats based on place, mode, and pace.

Flexibility Offered by Different Course Formats

Traditional Courses. Allen and Seaman (2008) defined traditional courses as 14- to 16-week courses that are delivered face to face. When examining the flexibility offered by different course formats, a traditional course provides minimal flexibility. The flexibility of a traditional course is constrained by several factors. To begin with, a traditional course is held at a specific place. Furthermore, the extent to which traditional courses make use of technology to deliver course content has increased over the past two decades (Haleem et al., 2022). However, technology only supports course content delivery in traditional courses. Conversely, technology is essential in hybrid and online courses as content cannot be delivered without it (Ahmed & Opoku, 2022). Finally, the pacing of a traditional course is limited because students must attend class sessions at certain times. In other words, access to some course content is bound to specific times.

In traditional courses, time windows are rigid. Students typically attend two to three class sessions a week. These sessions are the only time windows in which students can access certain course content. In traditional courses, time windows open and close according to the start and end times of class sessions. Furthermore, the size of each time window corresponds to the length of each class session.

Online Courses. Allen and Seaman (2008) defined online courses as courses "in which at least 80 percent of the course content is delivered online" (p. 4). Compared to traditional courses, online 14- to 16-week courses provide greater flexibility. Using technology, more specifically web applications, the online mode of course delivery increases flexibility in terms of place and pace. Ganesh et al. (2015) stated that online courses and programs provide flexibility and convenience in course delivery. In terms of place, online courses are not bound to a specific location. Students can access course materials at any place that has the requisite technology for high-speed internet access.

Online courses increase flexibility in terms of pace. Unlike traditional courses, time windows need not open or close according to the start and end times of class sessions. Instead, time windows close according to assessment deadlines. Students are free to access course content anytime before corresponding assessment deadlines. Furthermore, the size of each time window is determined by the amount of information covered between assessment deadlines. For example, instead of attending a one-hour lecture at a specific time, students can access the lecture online at any time before the corresponding assessment deadline.

Face-to-Face Compressed Courses. Traditional courses and face-to-face compressed courses differ in terms of pace. Carman and Bartsch (2017) defined compressed courses as courses that have the same amount of contact time but are taught in a shorter timeframe than the traditional semester of 14 to 16 weeks. Compressed courses offer students the option to study when they are less busy. For example, if three 5-week courses are offered across a 15-week period, then students have the flexibility to attend the course that works best for their busy schedules. The pacing flexibility of compressed courses minimizes the potential for the competing responsibilities of non-traditional students, such as work or family obligations, to interrupt learning. Hanover Research (2018) asserted that:

> Accelerated [compressed] course scheduling in particular … can be beneficial for students who may be underprepared or very busy by helping to streamline the process and minimize the possibility of outside roadblocks. Indeed, when you accelerate [a] course from 15 weeks to 12, eight, or six weeks, there [is] less of a chance for life to get in the way of that course. (p. 20)

Online Compressed Courses. Lastly, online compressed courses are the most versatile format in terms of flexibility as the format offers a combination of benefits from both online courses and compressed courses. When the mode of course delivery is online, students can access course content at any place that has the requisite technology for high-speed internet access.

With regard to pace, all compressed courses tighten time constraints. However, when compressed courses are taught online, these time constraints loosen. In online compressed courses, time windows close according to assessment deadlines rather than the end times of class sessions. Therefore, students have the flexibility to access course content anytime before assessment deadlines.

It is important to note that the shorter duration of online compressed courses lessens the time between assessment deadlines. Compared to online 14- to 16-week courses, students in online compressed courses have less time to access course content. Even though the time windows for online compressed courses are not as wide, the shortened duration of online compressed courses minimizes the possibility that non-academic responsibilities become obstacles to learning. Non-academic responsibilities are less likely to impede academic progress because students have greater flexibility to enroll in courses when they are less busy.

Carman and Bartsch (2017) as well as Bryant et al. (2003) insisted that increased flexibility through the use of compressed courses, online courses, or online compressed courses would enhance student retention and academic performance, especially for nontraditional students. The following chapter begins with a review of literature on how these courses are related to student outcomes and ends with a review of literature on how this relationship may vary according to student and course characteristics.

Chapter 2: Literature Review

Student Retention and Academic Performance in Compressed Courses

Research demonstrated that compressed courses have higher student retention rates than traditional 14- to 16-week courses (Sheldon & Durdella, 2009; Walker, 2017). Regarding academic performance, some studies showed that students enrolled in compressed courses scored significantly higher than their counterparts in traditional-length courses (Carman & Bartsch, 2017; Walker, 2017). Other studies showed that there was no significant difference between traditional-length and compressed courses in terms of student academic performance (Anastasi, 2007; Hicks, 2014).

Sheldon and Durdella (2009) studied how different course lengths influenced student retention rates across developmental courses in math, reading, and English at a large suburban community college. Their participants were undergraduate students enrolled in one or more developmental courses using either a compressed or traditional-length format. The study took place from spring 1998 to fall 2001. The researchers defined traditional-length courses as courses that were 15 to 18 weeks long while 6- to 8-week courses were considered compressed courses. However, the two formats had the same number of contact hours.

Sheldon and Durdella (2009) used course completion as a measure of student retention. More specifically, the course completion rate was calculated for the compressed format by dividing the number of students who earned a passing grade, A, B , C, or CR, by the total number of students who attempted the compressed courses, including students who did not pass or withdrew from the courses. The course completion rate for the traditional-length format was also calculated in the same fashion. The results demonstrated that students in the compressed courses completed their courses at a significantly higher rate than their peers in the traditional-length courses. This pattern was consistent across all three areas of developmental courses: math, reading, and English. Additionally, the same pattern persisted across participants of different ethnic, gender, and age groups.

Similar to Sheldon and Durdella (2009), Walker (2017) also examined how student retention was related to course length. Walker compared course completion rates between traditional-length and compressed courses at a community college. Walker used math courses at two different levels: basic and intermediate. Each course was offered in both 8-week and 16-week formats. Students enrolled in the 8-week courses met four times per week, and students enrolled in the 16-week courses met twice per week. The compressed and traditional length courses were comparable in terms of instructional hours, course objectives, topics covered, quizzes, and exams. The results showed that the course completion rate for students enrolled in the 8-week math course at the basic level (85.8%) was higher than that of students enrolled in the 16-week math course at the same level (76.5%). The results were similar regarding the intermediate math courses; the course completion rate for the 8-week course was 83.3% while the rate for the 16-week course was 73.5%.

In addition to investigating student retention, Walker (2017) also examined academic performance in relation to course length, using final exam scores as a measure of academic performance. The results demonstrated that the proportion of students who passed the final exam in the 8-week math course at the basic level (85.8%) was higher than that of students who passed the final exam in the 16-week math course at the basic level (79.8%). The same pattern appeared in the intermediate math courses; 66.7% of students passed the final exam in the 8-week math course while 59.1% of students in the 16-week math course passed the final exam.

Unlike Walker (2017), Carman and Bartsch (2017) focused solely on academic performance in their study of different course lengths. The same professor taught 19 sections of a statistics course over six years, from 2006 to 2012; eleven sections were taught in 15 weeks, and the other eight sections were taught in 8 weeks. In both formats, the professor used the same lectures, exams, and class materials. The results demonstrated that students in both formats were comparable in terms of cumulative GPA. On the first two exams, no significant difference was found in student academic performance between the 15-week and 8-week courses. However, students enrolled in the 8-week courses scored significantly higher on the last exam and received significantly higher final grades compared to their counterparts in the 15-week courses.

Student Retention and Academic Performance in Online Courses

Unlike research on compressed courses, research on online courses in higher education showed that online courses failed to increase student retention and academic performance. In most empirical studies on the effect of online courses on student retention, online courses produced significantly lower retention rates in comparison to face-to-face courses (Atchley et al., 2013; McLaren, 2004; Nelson, 2007; Xu & Jaggars, 2011). Regarding student academic performance in online courses, most studies demonstrated that there was no significant difference between online and face-to-face courses (Lyke & Frank, 2012; Nemetz et al., 2017).

Atchley et al. (2013) examined the influence of course delivery method, online versus face-to-face, on student retention at a public comprehensive university. The researchers first created a list of all the 16-week courses taught from fall 2004 to spring 2009. Then, they selected the courses that were taught in both online and face-to-face formats by the same professor during the same semester. The researchers used course completion as a measure of student retention and defined students who received a letter grade as retained and students who either dropped or withdrew from their courses as not retained. The results showed that the course completion rate for students in the online courses was significantly lower than that of students in the face-to-face courses.

Furthermore, McLaren (2004) studied the influence of online and face-to-face courses on student retention. Across five semesters, each of which was 16 weeks long, a single professor taught seven online and four face-to-face sections of the same undergraduate course, business statistics. In terms of course content and exams, both the online and face-to-face sections were comparable. McLaren categorized student behaviors related to retention into three different types: completing the course, dropping the course, and vanishing without dropping the course. The results showed that there was a statistically significant relationship between student retention (completed, dropped, or vanished) and the method of course delivery (online or face-to-face).

The course completion rate for students enrolled in the face-to-face sections was 91.4% while the rate for students in the online sections was only 53.3%. The dropout rate for students enrolled in the online sections was approximately 4.8 times greater than the rate for students in the face-to-face sections. Similarly, the vanishing rate for students enrolled in the online sections was approximately 3.3 times greater than the rate for students in the face-to-face sections.

Concerning the impact of online courses on student academic performance, no significant difference has been found between online and face-to-face courses. For example, Lyke and Frank (2012) examined which course delivery method (online or face-to-face) resulted in higher academic performance in a counseling course at a small public college. The same instructor taught two sections of the counseling course during the same semester; one section was taught online, and the other was taught face-to-face. In both sections, the instructor used the same multiple-choice quizzes to assess student academic performance. The results showed that there was no significant difference in student academic performance between the online and face-to-face sections.

Similarly, Nemetz et al. (2017) investigated the influence of two different course delivery methods (online and face-to-face) on the academic performance of undergraduate students. The same instructor taught seven sections of a survey course; four sections were delivered online, and the other three sections were delivered face-to-face. Both the face-to-face and online sections were comparable in terms of course content, instruction, assignments, exams, and projects. The results showed that students' final grades did not differ between the online and face-to-face sections.

In conclusion, compared to traditional courses, compressed courses produced greater student retention as well as comparable or higher academic performance (Carman & Bartsch, 2017; Sheldon & Durdella, 2009; Walker, 2017). Unlike compressed courses, online courses failed to increase student retention and academic performance. Compared to traditional courses, online courses yielded lower student retention and comparable academic performance (Atchley et al., 2013; Lyke & Frank, 2012; Nemetz et al., 2017).

Although both compressed courses and online courses provide students with greater flexibility than traditional courses, only compressed courses produced promising results related to student retention and academic performance (Carman & Bartsch, 2017; Sheldon & Durdella, 2009; Walker, 2017). The concept of marginal utility can provide a rationale for why only one of the two course formats yielded promising results. According to this concept, the amount people pay for an item corresponds to the utility the item provides (Kauder, 2015). Contextualizing marginal utility within the context of course format, "an item" represents a course format, "the utility [an] item provides" represents the flexibility offered by a course format, and "the amount people pay for an item" represents the challenges that a course format presents to students.

Nontraditional students asserted that flexible course formats allowed them to successfully manage their studies in concert with their nonacademic responsibilities (Crews & Butterfield, 2014). Taking these assertions into account, more flexible course formats are expected to provide nontraditional students with more utility. However, it is important to note that flexible course formats do not always improve student retention and academic performance. In order to positively influence student retention and academic performance, the flexibility offered by a given course format must exceed the challenges the course format presents to students.

Marginal utility can explain why the online course format failed to enhance student retention and academic performance in previous studies. The online format does increase flexibility; however, this increase is not greater than the challenges students must endure for the added flexibility. These challenges include: (a) feeling nervous about using technology, (b) leaving familiar face-to-face learning environments, and (c) feeling isolated as a result of difficulties interacting virtually with classmates and instructors (Gillett-Swan, 2017).

Along the same line, marginal utility can also explain why the compressed course format succeeded in enhancing student retention and academic performance in previous studies. The compressed format increases flexibility, and this increase exceeds the challenges students must endure to benefit from the added flexibility. These challenges include a heavier daily course workload, which is a consequence of a shorter semester, as well as mental and physical burnout (Daniel, 2000; Davies, 2006). However, since traditional courses and compressed courses share the face-to-face mode of course delivery, students in compressed courses do not have to navigate the challenges associated with online learning.

In summary, many empirical studies examined student retention and academic performance in either compressed or online courses, compared to traditional courses (Atchley et al., 2013; Carman & Bartsch, 2017; Lyke & Frank, 2012; McLaren, 2004; Nemetz et al., 2017; Sheldon & Durdella, 2009; Walker, 2017). However, few studies investigated student retention and academic performance in online compressed courses, compared to other types of courses, specifically traditional and online courses. Among studies that compared student retention and academic performance across different course formats, only a few studies conducted further analysis on how course formats interacted with student and course characteristics to influence student retention and academic performance. Before reviewing the studies that examined interactions, the following section describes the student and course characteristics that have been shown to affect student retention and academic performance.

Student and Course Characteristics Contributing to Student Outcomes

Major student characteristics that have been shown to affect student retention and academic performance were categorized into two groups: demographic (e.g., age) and academic (e.g., college GPA). Beginning with the demographic characteristic of age, older students achieved higher academic performance and were more likely to persist than younger students (Millea et al., 2018; Sheard, 2009). Concerning gender, female students outperformed male students in terms of both academic performance and student retention (Thiele et al., 2016). With respect to financial aid, Singell Jr (2004) found that while financial aid that did not require repayment (e.g., grants) increased student retention, financial aid that required repayment, either in the form of currency or labor (e.g., loans and work-study), decreased student retention. Furthermore, Stater (2009) found that any type of financial aid helped students achieve higher academic performance. Regarding enrollment status, part-time students underperformed full-time students in terms of both academic performance and student retention (Adelman, 1999; Feldman, 1993; Horn, 1998). Concerning first-generation status, first-generation college students achieved lower academic performance and were less likely to persist than college students who were not first generation (Lee et al., 2004; Nunez, 1998). In regard to ethnicity, students who identified themselves as White tended to perform slightly better than students who did not identify as White (Broecke & Nicholls, 2007; Jacobs, 2008; Richardson, 2008).

Moving onto academic characteristics, the characteristic that had a strong positive influence on student outcomes was cumulative or prior GPA (Brookshire & Palocsay, 2005; Nakajima et al., 2012). Brookshire and Palocsay (2005) found that prior GPA was the most significant predictor for course grade. Furthermore, Nakajima et al. (2012) found that the effect of cumulative GPA on student retention was significant and positive. Regarding remedial or developmental courses, students who took remedial courses were less likely to persist than students who did not take remedial courses (Stewart et al., 2015). Furthermore, students who took remedial courses rarely achieved higher academic performance when compared to students who did not take remedial courses (Sanabria et al., 2020). Concerning the type of secondary education credential earned, GED recipients performed more poorly than high school diploma recipients in terms of student retention and academic performance (Hewitt et al., 2019; Islam & Rouse, 2021).

The final characteristic contributing to student outcomes focuses on course difficulty. Course difficulty has been shown to affect student retention and academic performance (Tomkin & West, 2022; Wladis et al., 2017). It should be noted that course difficulty was defined differently across the literature reviewed. Some studies approached course difficulty using intensity. Courses like writing-intensive (WI) or science, technology, engineering, and math (STEM) courses were considered to be more difficult. Course intensity was found to negatively influence student retention and academic performance. For example, Tomkin and West (2022) found that students who took STEM courses earned significantly lower grades and GPAs when compared to students who took non-STEM courses. Wladis et al. (2017) approached course difficulty using course level. Wladis et al. asserted that courses requiring prerequisites (i.e., 200-level courses or above) were more difficult as they covered more advanced topics than lower-level courses (i.e., 100-level courses). Wladis et al. found that students in the less difficult 100-level courses performed more poorly than students who took the more difficult 200-level courses. Wladis et al. attributed the result to the fact that course level was closely related to years of study. Urtel (2008) found that years of study positively affected student outcomes.

Thus far, I have discussed student and course characteristics contributing to student retention and academic performance. A few studies investigated if the effects of some of these characteristics significantly varied between online and face-to-face course formats in terms of student retention and academic performance. These studies included the following student and course characteristics: gender, ethnicity, age, enrollment status (i.e., part-time versus full-time), prior GPA, elective versus required courses, and STEM versus non-STEM courses.

The Effects of Student and Course Characteristics Across Course Formats

Beginning with the student characteristic of ethnicity, the performance discrepancy between Black and White students in online courses was significantly greater than the performance discrepancy between Black and White students in face-to-face courses (Xu & Jaggars, 2014). It is important to note that the term "performance discrepancy" refers to a discrepancy in both student retention and academic performance. Xu and Jaggars (2014) found that all ethnic groups represented among their participants, including Asian, Black, Hispanic, and White, performed more poorly in online courses when compared to their peers from the same ethnic group in face-to-face courses in terms of student retention and academic performance. Similarly, Kaupp (2012) found that both White and Hispanic students in online courses performed less well than their ethnic peers in face-to-face courses. However, Urtel (2008) found that Hispanic and Black students in online courses did not perform differently from their ethnic peers in face-to-face courses.

Concerning gender, its effect on student retention significantly varied between online and face-to-face courses (Xu & Jaggars, 2014). More specifically, the discrepancy in retention between female and male students in online courses was significantly greater than the discrepancy in retention between female and male students in face-to-face courses. Xu and Jaggars (2014) found that in online and face-to-face courses, female students were more likely to persist than male students. They also found that female and male students were less likely to persist in online courses when compared to their peers from the same gender group in face-to-face courses.

Furthermore, Urtel (2008) found that female students in online courses earned significantly lower grades when compared to female students in face-to-face courses. However, for male students, there was no significant difference between online and face-to-face courses in terms of academic performance. Urtel also found that in online and face-to-face courses, the academic performance of female students did not significantly differ from the academic performance of male students. Lastly, Figlio et al. (2010) found that female students in online courses performed as well as female students in face-to-face courses. On the other hand, male students in online courses underperformed male students in face-to-face courses.

In regard to age, its effect on student retention and academic performance significantly varied between online and face-to-face courses (Xu & Jaggars, 2014). More specifically, the performance discrepancy between older and younger students in online courses was significantly smaller than the performance discrepancy between older and younger students in face-to-face courses. Both older and younger students in online courses performed more poorly than their peers from the same age group in face-to-face courses in terms of student retention and academic performance. Additionally, older students were less likely to persist than younger students in face-to-face courses. While some studies demonstrated that older students in online courses achieved higher academic performance than older students in face-to-face courses, other studies showed that there was no correlation between student age and academic performance (Dille & Mezack, 1991; Souder, 1993; Urtel, 2008).

With respect to prior GPA, its effect on student retention and academic performance significantly varied between online and face-to-face courses (Xu & Jaggars, 2014). More specifically, the performance discrepancy between students with higher prior GPAs and students with lower prior GPAs in online courses was significantly smaller than the performance discrepancy between students with higher prior GPAs and students with lower prior GPAs in face-to-face courses. Both students with lower prior GPAs and students with higher prior GPAs performed more poorly in online courses than their respective counterparts in face-to-face courses regarding student retention and academic performance. However, Figlio et al. (2010) found that students with higher prior GPAs in online courses did not perform differently from students with higher prior GPAs in face-to-face courses.

Transitioning from student characteristics to course characteristics, Wladis et al. (2014a) examined elective courses versus required courses and found that students who took elective courses in the online format were less likely to persist than students who took elective courses in the face-to-face format. However, for students who took required courses, there was no significant difference between the online and face-to-face course formats in terms of student retention. In their later study, Wladis et al. (2017) found that the performance discrepancy between students who took elective courses in the online format and students who took elective courses in the face-to-face format was significantly greater than the performance discrepancy between students who took required courses in the online format and students who took required courses in the face-to-face format.

With respect to STEM versus non-STEM courses, Wladis et al. (2014b) found that students who took STEM courses in the online format were less likely to persist than students who took non-STEM courses in the online format. Unfortunately, studies concerning online STEM courses often concentrated on a single course and did not compare STEM courses to non-STEM courses (Kartha, 2006; Reuter, 2009).

So far, I have discussed studies that investigated how student and course characteristics interacted with different course formats to influence student outcomes. The studies reviewed only included two course formats, online and face-to-face. Overall, these studies demonstrated that regardless of student and course characteristics, students in online courses either performed more poorly than or did not perform differently from students in face-to-face courses.

Need and Significance of the Study

Many empirical studies examined student retention and academic performance in either online or compressed courses, compared to face-to-face courses (Atchley et al., 2013; Carman & Bartsch, 2017; Lyke & Frank, 2012; McLaren, 2004; Nemetz et al., 2017; Sheldon & Durdella, 2009; Walker, 2017). However, few studies investigated student retention and academic performance in online compressed courses, compared to other types of courses, specifically face-to-face and online courses.

It is a worthy topic of study to explore student retention and academic performance in online compressed courses, compared to other types of courses. When I examined the flexibility offered by different course formats, online compressed courses produced the widest variety of flexibility by combining benefits from both compressed courses and online courses. By offering heightened flexibility, online compressed courses may attenuate the difficulties associated with online courses in terms of student retention and academic performance.

After reviewing two bodies of literature, research on compressed courses and research on online courses (Atchley et al., 2013; Carman & Bartsch, 2017; Lyke & Frank, 2012; Nemetz et al., 2017; Sheldon & Durdella, 2009; Walker, 2017; Xu & Jaggars, 2011), I hypothesized that the abundance of flexibility in compressed courses would compensate for the deficit of flexibility in online courses. Compressed courses had an abundance of flexibility as the flexibility offered by these courses was greater than the related challenges. Conversely, online courses had a deficit of flexibility as the flexibility offered by these courses did not exceed the related challenges. When combining these two types of courses, I hypothesized that student outcomes in online compressed courses would be similar to or better than those in face-to-face courses. In other words, students in online compressed courses were hypothesized to perform as well as or outperform their peers in face-to-face courses regarding student retention and academic performance.

The purpose of this study was to compare student retention and academic performance across the following three course formats: traditional (16-week face-to-face), online (16-week online), and online compressed (5-week online). The current study also investigated how these course formats interacted with student and course characteristics to influence student outcomes. More exactly, this study examined if the effects of student and course characteristics on student outcomes varied across the different course formats. As course completion and final grade are fundamental measures of success for community college students (Xu & Jaggars, 2014), I used them as the measures for student outcomes in this study. I used course completion to measure student retention and final grade to measure academic performance. In this study, there were two research questions and six sub-questions for each research question:

1. Which course format leads to higher student academic performance?

   (1) Does the effect of ethnicity on student academic performance vary across the different course formats?

   (2) Does the effect of course difficulty (STEM versus non-STEM) on student academic performance vary across the different course formats?

   (3) Does the effect of age on student academic performance vary across the different course formats?

   (4) Does the effect of cumulative GPA on student academic performance vary across the different course formats?

   (5) Does the effect of gender (female versus male) on student academic performance vary across the different course formats?

   (6) Does the effect of enrollment status (part-time versus full-time) on student academic performance vary across the different course formats?

2. Which course format leads to greater student retention?

   (1) Does the effect of ethnicity on student retention vary across the different course formats?

   (2) Does the effect of course difficulty (STEM versus non-STEM) on student retention vary across the different course formats?

   (3) Does the effect of age on student retention vary across the different course formats?

   (4) Does the effect of cumulative GPA on student retention vary across the different course formats?

   (5) Does the effect of gender (female versus male) on student retention vary across the different course formats?

(6) Does the effect of enrollment status (part-time versus full-time) on student retention vary across the different course formats?

Based on the literature reviewed regarding the online course format (Atchley et al., 2013; Lyke & Frank, 2012; Nemetz et al., 2017; Xu & Jaggars, 2011), I hypothesized that in this study, the 16-week online course format would produce significantly lower student retention and similar academic performance when compared to the traditional course format. I also hypothesized that student outcomes in the 5-week online course format would be similar to or better than those in the traditional course format based on two bodies of literature, research on compressed courses and research on online courses (Atchley et al., 2013; Carman & Bartsch, 2017; Lyke & Frank, 2012; Nemetz et al., 2017; Sheldon & Durdella, 2009; Walker, 2017; Xu & Jaggars, 2011). In other words, students in the 5-week online course format were hypothesized to perform as well as or outperform their peers in the traditional course format regarding student retention and academic performance.

Finally, I hypothesized that in this study, regardless of student and course characteristics, students in the 16-week online course format would perform more poorly than or similar to their peers in the traditional course format in terms of student retention and academic performance. This hypothesis was based on the literature reviewed regarding how online and face-to-face course formats interacted with student and course characteristics to influence student outcomes (Figlio et al., 2010; Kaupp, 2012; Urtel, 2008; Wladis et al., 2014a; Xu & Jaggars, 2014).

Chapter 3: Methods

Study Design

Multilevel modeling was employed as a statistical framework reflecting the hierarchical structure of the data used for the current study. There were three levels in the data; the first level was nested within the second level, and the second level was nested within the third level. At the first level, students were the unit of analysis, and at the second level, course sections were the unit of analysis. Lastly, at the third level, instructors were the unit of analysis. According to Hox (2017), multilevel modeling enables researchers to study nested relationships, and individuals nested within the same group tend to be more homogenous than individuals nested within other groups. It should be noted that the effects of predictors depend on higher-level units within nested data. If nested relationships were ignored, then the effects of predictors could be easily misrepresented. Furthermore, the errors of individuals nested within the same group are correlated. Therefore, single-level regression cannot be used as it assumes that errors are independent (Raudenbush & Bryk, 2002).

Taking into account the hierarchical structure of the data, I utilized three-level models. This three-level design can be described as a mixed-effects analysis of variance examining the academic performance and persistence of students (level 1) in their course sections (level 2) taught by their instructors (level 3). It is important to note that each instructor taught several sections of their respective course, and these sections covered three formats: traditional (16-week face-to-face), online (16-week online), and online compressed (5-week online). The three-level design investigated the variation of student retention and academic performance in relation to the three course formats. This design also controlled for possible instructor-related variation as each instructor included in the current study taught their respective course across all three formats.

Setting

This study took place within the University of Hawaiʻi Community College (UHCC) system. The UHCC system is composed of seven public community colleges: (a) Hawaiʻi Community College (HawCC), (b) Honolulu Community College (HCC), (c) Kapi'olani Community College (KapCC), (d) Kaua'i Community College (KCC), (e) Leeward Community College (LCC), (f) University of Hawaiʻi Maui College (UHMC), and (g) Windward Community College (WCC). Based on information provided by the University of Hawaiʻi Institutional Research and Analysis Office (UH-IRAO), I averaged UHCC system data from 2018 to 2021. Over this period, an average of 25,900 students enrolled in the UHCC system each semester, excluding summer, and about 67% of them enrolled part time. The average student was 25 years old, and female students outnumbered male students, 57% to 43%. On average, the UHCC system provided students with 170 certificate programs and 126 associate degree programs; similar programs offered by different colleges were counted separately. Additionally, the UHCC system offered approximately 3,650 classes each semester, excluding summer sessions.

Participants

Instructors

I requested and obtained data from the UH-IRAO. The data included 51 instructors who taught 30 different subjects across the UHCC system from spring 2018 to spring 2021. This 3-year time span was necessary to ensure that each instructor taught their respective course in all three formats. The courses they taught covered 30 subjects, including art, biology, business, communications, economics, education, English, geography, Hawaiian studies, history, math, philosophy, psychology, sociology, speech, and women's studies. On average, each instructor taught 19 sections of their respective course during the 3-year study period. For each instructor, at least one of their sections was delivered in the 16-week face-to-face format, at least one was delivered in the 16-week online format, and at least one was delivered in the 5-week online format.

In total, the 51 instructors taught 1,003 course sections from spring 2018 to spring 2021. More specifically, they taught 318 sections in the 16-week face-to-face format, 475 sections in the 16-week online format, and 210 sections in the 5-week online format. Among the 1,003 sections, 689 sections were taught at LCC, 134 sections were taught at HCC, 62 sections were taught at WCC, 58 sections were taught at UHMC, 31 sections were taught at KCC, 15 sections were taught at KapCC, and 14 sections were taught at HawCC.

Students

The data that I requested and obtained from the UH-IRAO included 22,280 students who were enrolled in 1,003 course sections that were taught by the previously mentioned instructors from spring 2018 to spring 2021. All 22,280 students declared one of the seven community colleges within the UHCC system as their home institution. More specifically, 16,668 students were enrolled at LCC; 2,366 were enrolled at HCC; 1,322 were enrolled at WCC; 885 were enrolled at UHMC; 454 were enrolled at KCC; 352 were enrolled at KapCC; and 233 were enrolled at HawCC. Furthermore, all 22,280 students were able to take courses in any format offered as none of them were enrolled in an online degree program. In the data I received, most students who took courses in the 5-week online format also took courses in other formats at the same time.

The mean age of the 22,280 students was 25 years old, and their ages ranged from 14 to 75. The students who received a Pell Grant accounted for 34% of the 22,280 students. There were slightly more full-time students than part-time students, 53% versus 47%. Of the 21,665 students for whom there were data on gender, 65% were female and 35% were male. Among the 22,150 students for whom there were data on ethnicity, 29% were Native Hawaiian, 20% were Filipino, 15% were mixed race, 10.9% were Caucasian/White, 9.8% were other Asian (i.e., neither Filipino nor East Asian), 8.2% were East Asian, 2.2% were Pacific Islanders, 2% were African American/Black,1.8% were Hispanic, and 0.3% were Native American. For more information on the student participants, see the "Student-Level Predictors" heading in Table 1.

Table 1

Descriptive Statistics for Courses and Students

Predictor	N	Frequency	Proportion or Mean	Standard Deviation
Course-Level Predictors				
Course Format	1,003			
Online5		210	0.209	
Online16		475	0.474	
F2F		318	0.317	
Course Difficulty				
STEM	1,003	146	0.146	
WI	1,003	62	0.062	
Level	1,003	161	0.161	
Student-Level Predictors				
Academic				
Remedial Math	22,280	7,495	0.336	
Remedial English	22,280	845	0.038	
CGPA	22,253		2.251	1.478
Demographic				
Age	22,280		24.755	8.28
Female	21,665	14,148	0.653	
1stGen	22,280	5,188	0.233	
Pell	22,280	7,647	0.343	

Part-Time	22,280	10,522	0.472
GED	21,745	473	0.022
Work-Study	22,280	136	0.006
Ethnicity	22,150		
NativeHI		6,456	0.29
Filipino		4,486	0.201
Black		445	0.02
Hispanic		412	0.018
Caucasian/White		2,435	0.109
East Asian		1,819	0.082
Native American		71	0.003
Pacific Islander		498	0.022
Other Asian		2,178	0.098
Mixed-Race		3,350	0.15

Variables

Outcome Variables

Academic Performance. I used students' final grades as a measure of academic performance. I coded a grade of A as 4, B as 3, C as 2, D as 1, and F as 0. Regarding a grade of CR (credit), I coded it as 2, the same as a C grade, because students needed to attain a C grade or higher to receive a CR grade (UHCC, n.d.). Similarly, I coded a grade of NC (no credit) as 0, the same as an F grade, because an NC grade was assigned for performance that would have earned a D or F grade.

Furthermore, I coded a grade of N (no grade) as 0, the same as an F grade as both these grades were defined as failure to demonstrate a minimal level of academic accomplishment (UHCC, n.d.). It is important to note that I removed students who earned a grade of L (audit), W (withdrawal), or I (incomplete) from the analysis of academic performance because these grades did not demonstrate how students performed academically.

As a result, 1,441 students were removed, and the remaining 20,839 students were used in the analysis of academic performance.

Student Retention. I utilized course completion as a measure of student retention. According to Hagedorn (2006), "The smallest unit of analysis with respect to retention is that measured by course completion" (p. 16). It is defined as completing a course with a passing grade. Since a D grade was the minimum passing grade within the UHCC system (UHCC, n.d.), I coded a grade of D or higher, including a CR grade, as 1. Similarly, I coded grades lower than a D (F, N, and NC) as 0. Furthermore, I coded I and W grades as 0 as they indicated that students failed to complete their courses. It should be noted that I removed students who earned a grade of L from the analysis of student retention because this grade did not demonstrate whether or not students completed their courses. As a result, three students were removed, and the remaining 22,277 students were used in the analysis of student retention.

Predictor Variables

CGPA. The cumulative grade point average (CGPA) variable represents a student's cumulative GPA, ranging from 0.00 to 4.00. For example, if a student took Math 100 in spring 2020, I used the student's cumulative GPA from fall 2019.

Age. The age variable represents a student's age, ranging from 14 to 75. Each student's age was calculated based on the student's birth year.

Female. The female variable represents a student's gender. Female students were coded as 1, and male students were coded as 0.

Part-Time. The part-time variable represents a student's enrollment status. Part-time students were coded as 1, and full-time students were coded as 0.

Pell. The Pell variable represents a student's Pell Grant status. Pell Grant recipients were coded as 1, and students who did not receive the grant were coded as 0.

1stGen. The 1stGen variable represents a student's first-generation status. First-generation students were coded as 1, and students who were not first generation were coded as 0.

Remedial Math. The remedial math variable represents whether a student took any remedial math course. If students took any remedial math courses, then they were coded as 1, If not, they were coded as 0.

Remedial English. The remedial English variable represents whether a student took any remedial English course. If students took any remedial English courses, then they were coded as 1. If not, they were coded as 0.

GED. The General Educational Development Test (GED) variable represents whether a student earned a high school diploma or a GED. GED recipients were coded as 1, and high school diploma recipients were coded as 0.

Work-Study. The work-study variable represents whether a student was a federal work-study recipient. If students received federal work-study grants, then they were coded as 1. If not, they were coded as 0.

Ethnicity. Originally, there were more than 20 ethnic categories in the data set. However, some categories only included a few students. Thus, I consolidated these smaller categories based on similar characteristics, such as geographic location. As a result, the ethnic categories were reduced to 10. The categorical variable of ethnicity was dummy coded into nine dichotomous variables with Caucasian/White serving as the reference group. As outlined by Alkharusi (2012), this coding process was necessary for adding ethnicity, an independent variable with more than two categories, to the regression equations in this study. The nine dichotomous variables are as follows:

NativeHI. The NativeHI variable represents whether a student is Native Hawaiian. Native Hawaiian students were coded as 1, and students of other ethnicities were coded as 0.

Black. The Black variable represents whether a student is Black/African American. Black/African American students were coded as 1, and students of other ethnicities were coded as 0.

Hispanic. The Hispanic variable represents whether a student is Hispanic. Hispanic students were coded as 1, and students of other ethnicities were coded as 0.

Filipino. The Filipino variable represents whether a student is Filipino. Filipino students were coded as 1, and students of other ethnicities were coded as 0.

East Asian. The East Asian variable represents whether a student is Chinese, Japanese, or Korean. East Asian students were coded as 1, and students of other ethnicities were coded as 0.

Other Asian. The other Asian variable represents whether a student is Asian but neither Filipino nor East-Asian. Other Asian students were coded as 1, and students of other ethnicities were coded as 0.

Pacific Islander. The Pacific Islander variable represents whether a student is a Pacific Islander, other than Native Hawaiian. Pacific Islander students were coded as 1, and students of other ethnicities were coded as 0.

Mixed-Race. The mixed-race variable represents whether a student is mixed race. Students who identified themselves as mixed race were coded as 1, and students who did not identify as mixed race were coded as 0.

Native American. The Native American variable represents whether a student is Native American. Native American students were coded as 1, and students of other ethnicities were coded as 0.

Course Format. Similar to ethnicity, course format was an independent variable with more than two categories. Course format had the following three categories: 5-week online, 16-week online, and 16-week face-to-face. As outlined by Alkharusi (2012), the categorical variable of course format was dummy coded into two dichotomous variables with the 16-week face-to-face format serving as the reference group. The two dichotomous variables are as follows:

Online5. The online5 variable represents a course that was delivered in the 5-week online format. Five-week online courses were coded as 1. Courses that were not delivered in this format were coded as 0.

Online16. The online16 variable represents a course that was delivered in the 16-week online format. Sixteen-week online courses were coded as 1. Courses that were not delivered in this format were coded as 0.

STEM. The STEM variable represents whether a course was a science, technology, engineering, or mathematics (STEM) course. STEM courses were coded as 1, and all other courses were coded as 0.

WI. The WI variable represents whether a course was a writing-intensive (WI) course. WI courses were coded as 1, and all other courses were coded as 0.

Level. The level variable represents whether a course was at the 200-level. Courses at the 200-level were coded as 1, and all other courses (i.e., 100-level courses) were coded as 0.

Variables With Missing Values

Variables with a high frequency of missing values were removed from the analysis. For example, I removed the high school GPA variable from the analysis because more than 80% of the values were missing. Among the variables included in the analysis, four variables had missing values. Less than 1% of the values for both the CGPA and ethnicity variables were missing. Similarly, values for both the female and GED variables were missing less than 3% of the time.

Data Analysis

I conducted multilevel modeling to address two sets of research questions in this study. For each set, I constructed four multilevel models, using IBM SPSS Statistics 25.0. Reflecting the hierarchical structure of the data, all eight models were three-level models. Models 1 to 4 addressed the first set of research questions, regarding student academic performance. Models 5 to 8 addressed the second set of research questions, concerning student retention. According to Hox (2017), in multilevel analysis, the first model (i.e., the baseline model) is constructed without predictors and each subsequent model builds upon its predecessor. Following the directions of Hox, I developed four sequential models for academic performance and four sequential models for student retention.

Chapter 4: Statistical Models

This chapter first describes single-level models, more specifically binary and ordinal logistic regression models. Understanding these simpler models is important as they serve as the foundation for the three-level models used in this study. After examining the single-level models, this chapter concludes with a detailed explanation of the study's three-level models.

Single-Level Models

Binary Logistic Regression Model

A binary logistic regression model is used when the outcome variable *Y* is binary, indicating that it only has two possible values (e.g., male/female). These values are typically coded as 0 and 1 (Fritz & Berger, 2015). According to Aldrich and Nelson (1984), in order to model a binary outcome variable as a linear combination of the predictor variables, the outcome variable is transformed into a logit, which is also known as a log odds. This transformation process has several steps. The first step is to transform a binary outcome variable, which has a value of either 0 or 1, into the probability for observing 1, which is denoted as $P(Y=1)$. This probability can take any value between 0 and 1. The second step is to transform the probability into the odds, $\frac{P}{1-P}$, which can take any positive value. The final step is to transform the odds into the logit, $ln\left(\frac{P}{1-P}\right)$, which can take any negative or positive value. In the binary logistic regression model below, the logit can take any numeric value and is linearly related to the predictor variable:

$$ln\left(\frac{P}{1-P}\right) = \alpha + \beta X$$

Ordinal Logistic Regression Model

An ordinal logistic regression model is used when the outcome variable *Y* is ordinal, indicating that it has three or more categories that can be ordered (e.g., low, medium, and high) (Bender & Grouven,1997; Hadi & Chatterjee, 2015). One way to model an ordinal outcome variable is to use cumulative logits. A cumulative logit, $ln\left(\frac{P(Y\leq c)}{P(Y>c)}\right)$, is constructed by dividing $P(Y \leq c)$, which represents the probability for being at or below a category (*c*) by $P(Y > c)$, which represents the probability for being above a category (*c*). It is important to note that *c* can represent any outcome category except for the last category, *k*+1, which is the reference category.

An ordinal logistic regression model assumes that an ordinal outcome variable (*Y*) is associated with an underlying latent continuous variable (η) through the concept of threshold (θ) (Bender & Grouven,1997; Hadi & Chatterjee, 2015). The ordered categories of *Y* exist on a continuum (η), and η is divided by threshold values. More specifically, thresholds are cut-points between the observed categories of an ordinal outcome variable. The number of thresholds is one less than the number of outcome categories. In the example below, there is an ordinal outcome variable with three categories, low (0), medium (1), and high (2):

$Y = 0$ if $\eta \leq \theta_1$

$Y = 1$ if $\theta_1 < \eta \leq \theta_2$

$Y = 2$ if $\theta_2 < \eta$

If η is less than or equal to the first threshold (θ_1), then the low category (0) of the outcome variable would be observed. If η is greater than the first threshold but less than or equal to the second threshold (θ_2), then the medium category (1) would be observed. Finally, if η is greater than the second threshold, then the high category (2) would be observed.

$$\eta_c = ln\left(\frac{P(Y\leq c)}{P(Y>c)}\right) = \theta_c - \beta x, \quad c = 1, \ldots, k$$

In the ordinal logistic regression model above, the threshold acts as the intercept. To be more exact, the threshold is the negative of the intercept. In this model, the slope or the coefficient does not have the *c* subscript because the parallel regression assumption is met. In other words, the same slope is assumed across all outcome categories. Unlike the slope, the threshold is notated with the subscript *c*, indicating that there is a different intercept for each outcome category. It should be noted that there is a minus sign in front of the slope because in SPSS, an ordinal logistic regression model inverts the direction of the slope.

Three-Level Models

When working with data that has a hierarchical structure, researchers should consider employing multilevel models as these models enable researchers to analyze data at several levels (Leyland & Groenewegen, 2020). Taking into account the hierarchical structure of the data analyzed for this study, I designed three-level models. In a three-level model, level-1 units ($i = 1, \ldots, n_i$) are nested within level-2 units ($j = 1, \ldots, n_j$), and the level-2 units are nested within level-3 units ($k = 1, \ldots, n_k$) (Raman & Hedeker, 2005). In this study, students were nested within course sections, and the course sections were nested within instructors.

I utilized a total of eight models in this study. The eight models were split between two outcome variables. The outcome variable of the first four models was student academic performance, which was measured by the final grades of students. Since there were more than two final grade categories (A, B, C, etc.) and these categories could be ordered from the lowest grade to the highest grade, I constructed three-level ordinal logistic regression models. These models were based on the ordinal logistic regression model described in the previous section.

On the other hand, the outcome variable of the last four models in this study was student retention, which was measured by course completion. Since course completion only had two categories, completed (1) and failed to complete (0), I built three-level binary logistic regression models. These models were based on the binary logistic regression model described in the previous section. In the following sections, I first present four academic performance models and then present four student retention models.

Academic Performance Models

According to Hox (2017), in multilevel analysis, the first model is constructed without predictors and each subsequent model builds upon its predecessor. Following the directions of Hox, I developed the first model for academic performance without any predictors.

Model 1 (Baseline Model for Academic Performance)

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \le c)}{P(Y_{ijk} > c)}\right) = \beta_{0jk} + \theta_2 + \theta_3 + \theta_4 \qquad (1)$$

$$\beta_{0jk} = \beta_{00} + u_{0jk} \qquad (2)$$

$$\beta_{00k} = \gamma_{000} + v_{00k}. \qquad (3)$$

Equation 1 represents the first level in which the student is the unit of analysis, and Equation 2 represents the second level in which the course section is the unit of analysis. Equation 3 represents the third level in which the instructor is the unit of analysis. In Equation 1, η_{cijk} represents the predicted log odds of earning a specific final grade (*c*) for a student *(i*) in a course section (*j*) taught by an instructor (*k*). It is important to note that for model identification purposes, only the first threshold (β_{0jk}) was designed to vary across level-2 and level-3 units (Hox, 2017; Raudenbush & Bryk, 2002). The other thresholds (θ_2, θ_3, and θ_4) were treated as fixed parameters. If all the thresholds had varied across groups, then it would have been impossible to make meaningful comparisons between the groups as the outcome variable would have been defined differently. For example, one group might have -1.4 for the first threshold, -1.2 for the second, -0.8 for the third, and -0.2 for the fourth. The next group might have -2.0 for the first threshold, -1.8 for the second, -1.6 for the third, and -1.3 for the fourth, and so on.

Taking a closer look at the thresholds, the first threshold (β_{0jk}) represents the log odds of receiving an F grade. In other words, any value lower than or at the first threshold is an F grade. The second threshold (θ_2) represents the cumulative log odds of receiving a D or an F grade. In other words, any value lower than or at the second threshold is a D or an F grade. The third threshold (θ_3) represents the cumulative log odds of receiving a C, D, or an F grade. In other words, any value lower than or at the third threshold is a C grade or lower. Finally, the fourth threshold (θ_4) represents the cumulative log odds of receiving a B, C, D, or an F grade. In other words, any value lower than or at the fourth threshold is a B grade or lower.

It should be noted that in this study, I used the following three terms interchangeably: the log odds of earning a specific final grade, the log odds of academic performance, and the log odds of academic achievement. In Equation 2, β_{0jk} represents the mean log odds of student academic performance in a course section (*j*) taught by an instructor (*k*), and β_{00k} represents the mean log odds of academic achievement in course sections taught by an instructor (*k*). Furthermore, u_{0jk} represents the random effect at the second or course section level, and var(u_{0jk}) was assumed to be approximately normally distributed with a mean of 0 and constant variance $(0, \sigma^2_{uo})$.

In Equation 3, β_{00k} represents the mean log odds of academic achievement in course sections taught by an instructor (*k*), and γ_{000} represents the grand-mean log odds across all instructors. In addition, υ_{00k} represents the random effect at the third or instructor level, and var(υ_{00k}) was assumed to be approximately normally distributed with a mean of 0 and constant variance (0, $\sigma^2_{\upsilon_{00}}$). Through substitution, the combined model is as follows:

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \gamma_{000} + \theta_2 + \theta_3 + \theta_4 + \upsilon_{00k} + u_{0jk}.$$

Model 2 (Course Format Predictors for Academic Performance)

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \beta_{0jk} + \theta_2 + \theta_3 + \theta_4 \qquad \text{(1, repeated)}$$

$$\beta_{0jk} = \beta_{00k} + \beta_{01k}(online5_{jk}) + \beta_{02k}(onlin16_{jk}) + u_{0jk} \qquad \text{(4)}$$

$$\beta_{00k} = \gamma_{000} + \upsilon_{00k} \qquad \text{(3, repeated)}$$

$$\beta_{01k} = \gamma_{010} \qquad \text{(5)}$$

$$\beta_{02k} = \gamma_{020}. \qquad \text{(6)}$$

Note. Equation 1 represents the first or student level. Equation 4 represents the second or course section level. The remaining equations represent the third or instructor level.

Model 2 built upon Model 1 by adding two dichotomous predictors, $(online5_{jk})$ and $(onlin16_{jk})$, which were used to represent course format. As a categorical variable, course format in this study had the following three categories: 5-week online, 16-week online, and 16-week face-to-face. As outlined by Alkharusi (2012), I dummy coded the categorical variable of course format into two dichotomous variables, $(online5_{jk})$ and $(onlin16_{jk})$, which I included in Equation 4. In order to represent the 5-week online course format, I coded $(online5_{jk})$ as 1 and $(onlin16_{jk})$ as 0. Conversely, to represent the 16-week online course format, I coded $(online5_{jk})$ as 0 and $(onlin16_{jk})$ as 1. Lastly, to represent the 16-week face-to-face course format, I coded both $(online5_{jk})$ and $(onlin16_{jk})$ as 0.

After adding $(online5_{jk})$ and $(onlin16_{jk})$ to Equation 4, β_{00k} became the average log odds of student academic performance in 16-week face-to-face course sections taught by an instructor (*k*), and γ_{000} became the grand-mean log odds across instructors in the 16-week face-to-face course format. It is important to note that I investigated the random effects of $(online5_{jk})$ and $(onlin16_{jk})$ at the third or instructor level, but the effects of these two course formats were not found to vary across instructors. Therefore, the effects of $(online5_{jk})$ and $(onlin16_{jk})$ remained fixed at level 3 in Model 2 and the subsequent academic performance models (Models 3 and 4). As both the effect of the 5-week online course format and the effect of the 16-week online course format did not vary at the instructor level, I did not include υ_{10k} in Equation 5 and υ_{20k} in Equation 6. Through substitution, the combined model is as follows:

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \gamma_{000} + \theta_2 + \theta_3 + \theta_4 + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + \upsilon_{00k} + u_{0jk}.$$

Model 3 (Student-Background and Course-Difficulty Predictors for Academic Performance)

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \beta_{0jk} + \theta_2 + \theta_3 + \theta_4 + \beta_{1jk}(female_{ijk}) + \beta_{2jk}(CGPA_{ijk}) + \cdots + \beta_{pjk}(xp_{ijk}) \quad (7)$$

$$\beta_{0jk} = \beta_{00k} + \beta_{01k}(online5_{jk}) + \beta_{02k}(online16_{jk}) + \beta_{03k}(STEM_{jk}) + u_{0jk} \quad (8)$$

$$\beta_{1jk} = \beta_{10k} \quad (9)$$

$$\beta_{2jk} = \beta_{20k} \quad (10)$$

$$\beta_{pjk} = \beta_{p0k} \quad (11)$$

$$\beta_{00k} = \gamma_{000} + \upsilon_{00} \quad \text{(3, repeated)}$$

$$\beta_{10k} = \gamma_{100} \quad (12)$$

$$\beta_{20k} = \gamma_{200} \quad (13)$$

$$\beta_{p0k} = \gamma_{p00} \quad (14)$$

$$\beta_{01k} = \gamma_{010} \quad \text{(5, repeated)}$$

$$\beta_{02k} = \gamma_{020} \quad \text{(6, repeated)}$$

$$\beta_{03k} = \gamma_{030}. \quad (15)$$

Note. Equation 7 represents the first or student level. Equations 8 to 11 represent the second or course section level. The remaining equations represent the third or instructor level.

Model 3 built upon Model 2 by adding student-background and course-difficulty predictors, which have been shown to affect academic performance (Broecke & Nicholls, 2007; Brookshire & Palocsay, 2005; Feldman, 1993; Jacobs, 2008; Lee et al., 2004; Millea et al., 2018; Nunez, 1998; Richardson, 2008; Sheard, 2009; Stater, 2009; Thiele et al., 2016; Tomkin &West, 2022). It should be noted that 17 student-background predictors were found to be significant. However, only a few predictors were added to Equation 7 as examples. The first predictor used as an example was $(female_{ijk})$, which represents the gender of a student (*i*) in a course section (*j*) taught by an instructor (*k*). The second predictor used as an example was $(CGPA_{ijk})$, which represents the cumulative GPA of a student (*i*) in a course section (*j*) taught by an instructor (*k*). In Equation 7, (xp_{ijk}) could be any one of the 17 student-background predictors. It simply represents the last student-background predictor included in the equation. Each of the coefficients (i.e., β_{1j} to β_{pjk}) represents the effect of its corresponding predictor on the log odds of student academic performance. For example, the coefficient β_{1jk} represents the effect of student gender on the log odds of academic achievement.

For each student-background predictor in Model 3, a level-2 regression equation was created (see Equations 9 to 11). For example, Equation 9 was created for the gender predictor $(female_{ijk})$. Similarly, for each student-background predictor, a level-3 regression equation was created (see Equations 12 to 14). For example, Equation 12 was created for the gender predictor. Bates et al. (2015) stated that testing random variations without theoretical reasons leads to a multitude of problems, including over parameterization, the failure of convergence, and uninterpretable findings. Following guidance from Bates et al., in Model 2, I tested if the effects of the course format predictors (i.e., 5-week online and 16-week online) randomly varied across instructors. While the course format predictors were the main focus of this study, the student-background predictors were simply added to Model 3 as they have been shown to affect academic performance (Broecke & Nicholls, 2007; Brookshire & Palocsay, 2005; Feldman, 1993; Jacobs, 2008; Lee et al., 2004; Millea et al., 2018; Nunez, 1998; Richardson, 2008; Sheard, 2009; Stater, 2009; Thiele et al., 2016). Several related studies fixed the effects of student-background predictors across higher-level units (Wladis et al., 2014b, 2017). Following in the footsteps of these related studies and using the guidance of Bates et al., I fixed the effects of student-background predictors across higher-level units (i.e., there are no random variances in Equations 9 through 14).

While 17 student-background predictors were found to be significant in Model 3, only one of the three course-difficulty predictors significantly affected student academic performance. I initially added three course-difficulty predictors to Model 3: 200-level courses, writing-intensive (WI) courses, and STEM courses. However, the 200-level and WI course predictors were not found to be significant. As a result, they were dropped from the model, and only the STEM predictor, denoted as $(STEM_{jk})$, appears in Equation 8.

In Equation 8, β_{00k} represents the mean log odds of student academic performance in the 16-week face-to-face course sections taught by an instructor (k), excluding STEM course sections. Furthermore, β_{03k} represents the effect of STEM course sections on the log odds of student academic performance. Similar to the student-background predictors, I fixed the effect of the STEM predictor across higher-level units (i.e., Equation 15 does not include v_{30k}). Through substitution, the combined model is as follows:

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \gamma_{000} + \theta_2 + \theta_3 + \theta_4 + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + \gamma_{030}(STEM_{jk}) + \gamma_{100}(female_{ijk}) + \gamma_{200}(CGPA_{ijk}) + \cdots + \gamma_{p00}(xp_{ijk}) + v_{00k} + u_{0jk}.$$

Model 4 (Effects of Interactions Between Course Format Predictors and Selected Predictors on Academic Performance)

Model 4 built upon Model 3 by adding interactions between the two course format predictors (5-week online and 16-week online) and the six selected predictors (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM). These six predictors, except for enrollment status, were selected based on the literature reviewed (Figlio et al., 2010; Kaupp, 2012; Urtel, 2008; Wladis et al., 2014b; Xu & Jaggars, 2014). I selected the enrollment status predictor as it distinguishes nontraditional students from traditional students. According to the U.S. Department of Education, part-time students are considered nontraditional students (Gilardi & Guglielmetti, 2011).

The interactions added to Model 4 enabled me to investigate if the effects of the six selected predictors varied across the different course formats. It should be noted that to better understand the meaning of each interaction, I conducted separate analyses on each selected predictor, resulting in a total of six separate analyses. Interactions can be formulated with either random or fixed effects (Raudenbush & Bryk, 2002). Since the effects of the 5-week online and 16-week online course formats were not found to vary at the instructor level, the interactions were formulated with fixed effects in Model 4.

Until now, the equations have been laid out by level and then combined through substitution. However, I only presented the combined equations in Model 4 as most interactions in this model were cross-level interactions that could only be shown when all three levels were combined. An interaction between a level-2 predictor and a level-1 predictor is referred to as a cross-level interaction (Heck et al., 2012). For example, a cross-level interaction between the level-2 predictor for the 5-week online course format and the level-1 predictor for student gender was denoted as $(online5_{jk} * female_{ijk})$. As a result of conducting separate analyses on each selected predictor, I created six combined models (i.e., one combined model for each selected predictor). For example, the combined model below includes interactions for the student gender predictor. More specifically, this model was built upon Model 3 by adding the following two interactions: $(online5_{jk} * female_{ijk})$ and $(online16_{jk} * female_{ijk})$. For the other five combined models, all the components from the model below remain the same except for the two interaction terms.

$$\eta_{cijk} = ln\left(\frac{P(Y_{ijk} \leq c)}{P(Y_{ijk} > c)}\right) = \gamma_{000} + \theta_2 + \theta_3 + \theta_4 + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + \gamma_{030}(STEM_{jk}) + \gamma_{100}(female_{ijk}) + \gamma_{200}(CGPA_{ijk}) + \cdots + \gamma_{p00}(xp_{ijk}) + \gamma_{110}(online5_{jk} * female_{ijk}) + \gamma_{120}(online16_{jk} * female_{ijk}) + \upsilon_{00k} + u_{0jk}.$$

In Model 4, I investigated if the effects of the six selected predictors varied across the different course formats. In order to further investigate if the effects of the selected predictors were significant in each online course format (i.e., 16-week online and 5-week online) and if the effect of each online course format was significant for a focal group of students, I performed follow-up analyses on each selected predictor. For example, I performed a follow-up analysis on the gender predictor to examine if the following differences were significant:

1. The difference in academic performance between female students in the 5-week online course format and female students in the traditional course format
2. The difference in academic performance between female students in the 16-week online course format and female students in the traditional course format
3. The difference in academic performance between female and male students in the 5-week online course format
4. The difference in academic performance between female and male students in the 16-week online course format

In order to investigate if each of the four differences above was significant, I calculated the *t*-statistic, a ratio of the combined coefficient to its corresponding standard error (DeJong & Chen, 2023). To be more specific, for each difference, I first added one coefficient for the relevant interaction and one coefficient for the relevant main effect. Then, using this combined coefficient and the standard errors of the two relevant coefficients, I calculated the *t*-statistic. Lastly, I compared the *t*-statistic to the *t*-critical value.

Student Retention Models

While Models 1 through 4 focused on the first research question regarding student academic performance, Models 5 through 8, focused on the second research question concerning student retention. It is important to note that the first four models and the last four models shared the same structures. The structure of Model 5 mirrored the structure of Model 1 as both models did not include any predictors. The structure of Model 6 also mirrored Model 2 as both models included the same course format predictors, 5-week online and 16-week online. Furthermore, the structure of Model 7 mirrored Model 3 as both models included student-background and course-difficulty predictors. Lastly, the structure of Model 8 mirrored Model 4 as both models included interactions between the two course format predictors (5-week online and 16-week online) and the six selected predictors (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM).

All in all, the models for student retention (Models 5 to 8) were built in the same way as the models for academic performance (Models 1 to 4). In order to reduce redundant information, only the first model for student retention (Model 5) was described in detail as it was the basic building block of the remaining retention models. For Model 5, all the equations were laid out by level and all their components were explained. However, for each of the subsequent models, only the combined equation was shown and only its essential components were described.

Model 5 (Baseline Model for Student Retention)

$\eta_{ijk} = ln\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \beta_{0jk}$ (16)

$\beta_{0jk} = \beta_{00k} + u_{0j}$ (2, repeated)

$\beta_{00k} = \gamma_{000} + \upsilon_{00k}.$ (3, repeated)

As outlined in Hox (2017), I developed the first model for student retention without any predictors. Equation 16 represents the first level in which the student is the unit of analysis, and Equation 2 represents the second level in which the course section is the unit of analysis. Equation 3 represents the third level in which the instructor is the unit of analysis. In Equation 16, η_{ijk} represents the predicted log odds of course completion for a student (*i*) in a course section (*j*) taught by an instructor (*k*). In this study, I used the following three terms interchangeably: the log odds of course completion, the log odds of persistence, and the log odds of student retention.

In Equation 2, β_{0j} represents the mean log odds of student retention in a course section (*j*) taught by an instructor (*k*), and β_{00k} represents the mean log odds of student retention in course sections taught by an instructor (*k*). In addition, u_{0jk} represents the random effect at the second or course section level, and var(u_{0jk}) was assumed to be approximately normally distributed with a mean of 0 and constant variance (0, σ^2_{uo}).

In Equation 3, β_{00k} represents the mean log odds of student retention in course sections taught by an instructor (*k)*, and γ_{000} represents the grand-mean log odds across all the instructors. Lastly, υ_{00k} represents the random effect at the third or instructor level, and var(υ_{00k}) was assumed to be approximately normally distributed with a mean of 0 and constant variance (0, $\sigma^2_{\upsilon_{00}}$). Through substitution, the combined model is as follows:

$$\eta_{ijk} = ln\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \upsilon_{00k} + u_{0jk}.$$

Model 6 (Course Format Predictors for Student Retention)

$$\eta_{ijk} = ln\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + v_{00k} + u_{0jk}.$$

Building upon Model 5, I added two course format predictors, $(online5_{jk})$ and $(online16_{jk})$ to Model 6. It is important to note that I investigated the random effects of $(online5_{jk})$ and $(online16_{jk})$ at the third or instructor level. The results of this investigation demonstrated that the effects of $(online5_{jk})$ and $(online16_{jk})$ did not vary across instructors. Therefore, these effects remained fixed at level 3 in Model 6 and the subsequent retention models.

Model 7 (Student-Background and Course-Difficulty Predictors for Student Retention)

$$\eta_{ijk} = ln\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + \gamma_{030}(STEM_{jk}) +$$

$$\gamma_{100}(female_{ijk}) + \gamma_{200}(CGPA_{ijk}) + \cdots + \gamma_{p0}\ (xp_{ijk}) + v_{00} + u_{0jk}.$$

Model 7 built upon Model 6 by adding student-background and course-difficulty predictors, which have been shown to affect student retention (Broecke & Nicholls, 2007; Feldman, 1993; Jacobs, 2008; Lee et al., 2004; Millea et al., 2018; Nakajima et al., 2012; Nunez, 1998; Richardson, 2008; Sheard, 2009; Singell Jr, 2004; Stewart et al., 2015; Thiele et al., 2016). Like related studies (Wladis et al., 2014a, 2014b, 2017), I fixed the effects of these predictors across higher-level units, which was also consistent with the guidance of Bates et al. (2015). It should be noted that 14 student-background predictors were found to be significant for student retention in Model 7. Regarding the course-difficulty predictors, $(STEM_{jk})$, representing STEM course sections, had a significant influence on academic performance. However, none of the course-difficulty predictors were found to be significant for student retention. Despite this result, $(STEM_{jk})$ was retained in Model 7 to demonstrate that both student-related predictors and course-related predictors were considered in the design of this study.

Model 8 (Effects of Interactions Between Course Format Predictors and Selected Predictors on Student Retention)

Model 8 built upon Model 7 by adding interactions between the two course format predictors (5-week online and 16-week online) and the six selected predictors (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM). These six predictors, except for enrollment status, were selected based on the literature reviewed (Figlio et al., 2010; Kaupp, 2012; Urtel, 2008; Wladis et al., 2014b; Xu & Jaggars, 2014). I selected the enrollment status predictor as it distinguishes nontraditional students from traditional students (Gilardi & Guglielmetti, 2011).

The interactions added to Model 8 enabled me to investigate if the effects of the six selected predictors on student retention varied across the different course formats. It should be noted that these interactions were formulated with fixed effects because the effects of the 5-week online and 16-week online course formats were not found to vary at the instructor level. It should also be noted that to better understand the meaning of each interaction, I conducted separate analyses on each selected predictor, resulting in a total of six separate analyses. Subsequently, I created six combined models (i.e., one combined model for each selected predictor). For example, the combined model below includes interactions for the student gender predictor. More specifically, this model was built upon Model 7 by adding the following two interactions: $(online5_{jk} * female_{ijk})$ and $(online16_{jk} * female_{ijk})$. For the other five combined models, all the components from the model below remain the same except for the two interaction terms.

$$\eta_{ijk} = ln\left(\frac{\pi_{ijk}}{1-\pi_{ijk}}\right) = \gamma_{000} + \gamma_{010}(online5_{jk}) + \gamma_{020}(online16_{jk}) + \gamma_{030}(STEM_{jk}) + \gamma_{100}(female_{ijk}) + \gamma_{200}(CGPA_{ijk}) + \cdots + \gamma_{p00}(xp_{ijk}) + \gamma_{110}(online5_{jk} * female_{ijk}) + \gamma_{120}(online16_{jk} * female_{ijk}) + v_{00k} + u_{0jk}.$$

In Model 8, I explored if the effects of the six selected predictors on student retention varied across the different course formats. In order to further explore if the effects of the selected predictors were significant in each online course format (16-week online and 5-week online) and if the effect of each online course format was significant for a focal group of students, I performed follow-up analyses on each selected predictor. For example, I performed a follow-up analysis on the gender predictor to examine if the following differences were significant:

1. The difference in student retention between female students in the 5-week online course format and female students in the traditional course format
2. The difference in student retention between female students in the 16-week online course format and female students in the traditional course format
3. The difference in student retention between female and male students in the 5-week online course format
4. The difference in student retention between female and male students in the 16-week online course format

In order to investigate if each of the four differences above was significant, I used the *t*-statistic, a ratio of the combined coefficient to its corresponding standard error (DeJong & Chen, 2023). The combined coefficient consisted of a coefficient for the relevant interaction and a coefficient for the relevant main effect.

Chapter 5: Results

Results of Academic Performance Models

Results of Model 1

Model 1 consisted of four thresholds and two variance components (see Table 2). The first threshold was -2.084, representing the log odds of receiving an F grade. In other words, any value lower than or at this threshold was an F grade. Each of the remaining three thresholds represented the cumulative log odds of receiving a particular grade or lower. Therefore, any value equal to or less than the second threshold, -1.719, was a D grade or lower. Similarly, the threshold for a C grade or lower was -0.996, and the threshold for a B grade or lower was 0.013. These thresholds were used to calculate the probability of receiving a particular final course grade. To begin with, using the exponentiated log odds (exp β), in Table 2, the probability of receiving an F grade was calculated as 0.124/(1 + 0.124) = 0.110.

Table 2

Baseline Model for Academic Performance

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Thresholds					
First (F grade)	-2.084***	0.102	-2.288	-1.879	0.124
Second (D or lower)	-1.719***	0.101	-1.922	-1.515	0.179
Third (C or lower)	-0.996***	0.101	-1.199	-0.794	0.369
Fourth (B or lower)	0.013	0.101	-0.189	0.215	1.013
Variances					
Level-1	1				
Level-2	0.214***	0.019	0.179	0.255	
Level-3	0.485***	0.103	0.32	0.735	

Note. Level-1 variance was scaled to 1.00. †p < .10; *p < .05; **p < .01; ***p < .001.

Next, using 0.179 from the exp β column of Table 2, the cumulative probability of receiving a D grade or lower was calculated as 0.179/(1 + 0.179) = 0.152. Therefore, the probability of receiving a D grade was 0.042 (0.152 – 0.110), the difference between the cumulative probability of receiving a D grade or lower (0.152) and the probability of receiving an F grade (0.110). In the same manner, the probability of receiving a C grade was calculated as 0.118 (0.270 – 0.152) by subtracting the cumulative probability of receiving a D grade or lower (0.152) from the cumulative probability of receiving a C grade or lower (0.270). Similarly, the probability of receiving a B grade was calculated as 0.233 (0.503 – 0.270) by subtracting the cumulative probability of receiving a C grade or lower (0.270) from the cumulative probability of receiving a B grade or lower (0.503). Thus, the probability of receiving an A grade was 0.497 (1.0 – 0.503), the difference between the cumulative probability of receiving an A grade or lower (1.0) and the cumulative probability of receiving a B grade or lower (0.503). In sum, the probabilities of receiving A, B, C, D, and F grades were respectively 0.503, 0.233, 0.118, 0.042, and 0.110.

Regarding the variance components in Table 2, the results indicated that there was significant variability in the log odds of academic performance at the course section level (u_{0j} = 0.214, p < .001) and at the instructor level (v_{00k} = 0.485, p < .001). Despite these results, the Wald test of variability should be used cautiously in multilevel models as variances are not normally distributed (Hox, 2017). Therefore, the significance found at the course section and instructor levels should be interpreted as approximate.

Intraclass Correlation Coefficient. The intraclass correlation coefficient (ICC) for each level of Model 1 was calculated. As Model 1 was an ordinal model with a logit link, the variance at level 1 was approximately 3.29 (Hox, 2017). To begin with, the ICC for level 1 was calculated using $\rho = \sigma^2_{Level\,1}/(\sigma^2_{Level\,1} + \sigma^2_{Level\,2} + \sigma^2_{Level\,3})$. The results showed that the proportion of variance between students was 3.29/(3.29 + 0.214 + 0.485), or 0.825. Next, the ICC for level 2 was calculated using $\rho = \sigma^2_{Level\ 2}/(\sigma^2_{Level\ 1} + \sigma^2_{Level\ 2} + \sigma^2_{Level\ 3})$. The results showed that the proportion of variance between course sections was 0.214/(3.29 + 0.214 + 0.485), or 0.054. Lastly, the ICC for level 3 was calculated using $\rho = \sigma^2_{Level\ 3}/(\sigma^2_{Level\ 1} + \sigma^2_{Level\ 2} + \sigma^2_{Level\ 3})$. The results demonstrated that the proportion of variance between instructors was 0.485/(3.29 + 0.214 + 0.485), or 0.122. According to Heck et al. (2022), if the ICC is greater than 0.05, then there is substantial clustering. In this study, the Wald test and ICC values indicated that there was sufficient variability at the section and instructor levels to support the rationale for a three-level model.

Results of Model 2

Using Model 1 as a foundation, Model 2 added two course format predictors: the 5-week online course format and the 16-week online course format (notated as “Online 5” and “Online 16” respectively in Table 3). Regarding the 5-week online predictor, the log odds of earning a higher grade increased by 0.503 for students who took courses in the 5-week online format ($p < .001$) when compared to their peers who took courses in the traditional format (i.e., 16-week face-to-face), holding the other predictor constant. This change in the log odds indicated that the odds of earning a higher grade increased by 65.4%, or 1.654 times, for students who took courses in the 5-week online format when compared to their peers who took courses in the traditional format.

Table 3

Course Format Predictors for Academic Performance

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Course-Level Predictors					
Course Format					
Online5	0.503***	0.063	0.379	0.627	1.654
Online16	0.163***	0.047	0.07	0.256	1.177
Thresholds					
First (F grade)	-1.922***	0.105	-2.133	-1.712	0.146
Second (D or lower)	-1.557***	0.105	-1.767	-1.347	0.211
Third (C or lower)	-0.834***	0.104	-1.043	-0.626	0.434
Fourth (B or lower)	0.176†	0.104	-0.033	0.384	1.192
Variances					
Level-1	1				
Level-2	0.190***	0.018	0.157	0.229	
Level-3	0.481***	0.102	0.317	0.729	

Note. Level-1 variance was scaled to 1.00. $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Similar results were found for the 16-week online predictor. The log odds of earning a higher grade increased by 0.163 for students who took courses in the 16-week online format ($p < .001$) when compared to their peers who took courses in the traditional format, holding the other predictor constant. This change in the log odds indicated that the odds of earning a higher grade increased by 17.7%, or 1.177 times, for students who took courses in the 16-week online format when compared to their peers who took courses in the traditional format.

Results of Model 3

Building upon Model 2, Model 3 added student-background and course-difficulty predictors that have been shown to affect academic performance. The results of Model 3 are presented in Table 4. Consistent with the results of Model 2, the effect of the 5-week online course format remained significant in Model 3. The log odds of earning a higher grade increased by 0.383 for students in the 5-week online course format ($p < .001$) when compared to their peers in the traditional course format (i.e., 16-week face-to-face), holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased 1.467 times for students in the 5-week online course format when compared to their peers in the traditional course format. In contrast to the results of Model 2, after adding the student-background and course-difficulty predictors to Model 3, the effect of the 16-week online course format became statistically nonsignificant (-0.008, $p \geq .10$). In other words, there was no significant difference between the 16-week online course format and the traditional course format in terms of student academic performance.

Table 4

Student-Background and Course-Difficulty Predictors for Academic Performance

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Course-Level Predictors					
Course Format					
Online5	0.383***	0.067	0.252	0.514	1.467
Online16	-0.008	0.05	-0.106	0.09	0.992
Course Difficulty					
STEM	-0.444†	0.261	-0.967	0.08	0.642
Student-Level Predictors					
Academic					
Remedial Math	-0.436***	0.032	-0.499	-0.373	0.647
Remedial English	-0.239*	0.096	-0.428	-0.05	0.787
CGPA	0.336***	0.011	0.315	0.358	1.4

Demographic					
Age	0.020***	0.002	0.017	0.024	1.021
Female	0.298***	0.031	0.238	0.358	1.347
1stGen	-0.086**	0.034	-0.152	-0.021	0.917
Pell	0.060†	0.031	-0.001	0.121	1.062
Work-Study	0.418*	0.185	0.055	0.781	1.519
Part-Time	0.157***	0.031	0.096	0.219	1.17
Ethnicity					
NativeHI	-0.582***	0.051	-0.681	-0.482	0.559
Filipino	-0.203***	0.054	-0.309	-0.096	0.816
Black	-0.759***	0.102	-0.959	-0.558	0.468
Hispanic	-0.352***	0.109	-0.567	-0.138	0.703
East Asian	0.161*	0.07	0.024	0.298	1.175
Native American	-0.216	0.25	-0.706	0.274	0.806
Pacific Islander	-1.031***	0.099	-1.226	-0.837	0.357
Other Asian	-0.199**	0.063	-0.322	-0.075	0.82
Mixed-Race	-0.306***	0.056	-0.416	-0.195	0.737
Thresholds					
First (F grade)	-1.166***	0.128	-1.418	-0.913	0.312
Second (D or lower)	-0.784***	0.127	-1.036	-0.532	0.456
Third (C or lower)	-0.008	0.127	-0.26	0.243	0.992
Fourth (B or lower)	1.077***	0.127	0.825	1.329	2.936
Variances					
Level-1	1				
Level-2	0.200***	0.02	0.165	0.243	
Level-3	0.423***	0.091	0.277	0.646	

Note. Level-1 variance was scaled to 1.00. †$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

Among the course-difficulty predictors explored in this study, only one predictor, STEM course sections (notated as "STEM" in Table 4), was significant. The coefficient of the STEM predictor demonstrated that there was a significant decrease in the log odds of earning a higher grade for students who took STEM course sections (-0.444, $p < .10$) when compared to students who took non-STEM course sections, holding all other predictors constant. These log odds were equivalent to a 35.8% decrease in the odds of earning a higher grade for students who took STEM course sections when compared to students who took non-STEM course sections. The following sections describe the effects of student-background predictors, more specifically demographic and academic predictors.

Demographic Predictors. In regard to student demographic predictors, there were six notable results. First, concerning age, older students were more likely to earn higher final course grades than younger students (0.020, $p < .001$). Second, with respect to gender, there was a significant increase in the log odds of earning a higher grade for female students (0.298, $p < .001$) in comparison to male students, holding all other predictors constant. These log odds were equivalent to a 34.7% increase in the odds of earning a higher grade for female students when compared to male students. Third, regarding enrollment status, the log odds of earning a higher grade increased by 0.157 for part-time students ($p < .001$) when compared to full-time students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 17%, or 1.170 times, for part-time students when compared to full-time students. Fourth, concerning first-generation status, the log odds of receiving a higher grade were significantly lower for first-generation college students (-0.086 , $p < .01$) when compared to college students who were not first generation, holding all other predictors constant. When converting these log odds to odds, the odds of earning a higher grade decreased by 8.3%, or 0.917 times, for first-generation college students, compared to college students who were not first generation. Fifth, in regard to Pell

Grant eligibility, the log odds of earning a higher grade increased by 0.060 for Pell Grant recipients ($p < .10$) when compared to students who did not receive a Pell Grant, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 6.2%, or 1.062 times, for Pell Grant recipients when compared to students who did not receive a Pell Grant.

Finally, with respect to ethnicity, there was a significant increase in the log odds of earning a higher grade for East Asian students (0.161, $p < .05$) in comparison to White students, holding all other predictors constant. These log odds were equivalent to a 17.5% increase in the odds of earning a higher grade for East Asian students when compared to White students. Regarding all other ethnic groups included in the analysis, there was a significant decrease in the log odds of earning a higher grade when compared to White students, holding all other predictors constant: African American/Black students (-0.759, $p < .001$), Filipino students (-0.203, $p < .001$), Hispanic students (-0.352, $p < .001$), mixed-race students (-0.306, $p < .001$), Native Hawaiian students (-0.582, $p < .001$), other Asian students (-0.199, $p < .01$), and Pacific Islander students (-1.031, $p < .001$).

Academic Predictors. Concerning remedial math courses, there was a significant decrease in the log odds of earning a higher grade for students who previously took remedial math courses (-0.436, $p < .001$) when compared to students who did not previously take remedial math courses, holding all other predictors constant. These log odds were equivalent to a 35.3% decrease in the odds of earning a higher grade for students who previously took remedial math courses when compared to students who did not. Similar results were found for remedial English courses. The log odds of earning a higher grade decreased by 0.239 for students who previously took remedial English courses ($p < .05$) when compared to students who did not previously take remedial English courses, holding all other predictors constant. This result indicated that the odds of earning a higher grade decreased by 21.3%, or 0.787 times, for students who previously took remedial English courses when compared to students who did not.

Regarding cumulative GPA, a 1-point increase in a student's cumulative GPA was associated with a 0.336 increase in the log odds of earning a higher grade ($p < .001$) while holding all other predictors constant. When converting these log odds to odds, a 1-point increase in a student's cumulative GPA was associated with a 40% increase in the odds of earning a higher grade, holding all other predictors constant.

Finally, in order to examine the extent to which the predictors of Model 3 reduced error, I calculated the proportional reduction in error (PRE) at the second and third levels. The results of this study demonstrated that when compared to the baseline model (Model 1), the all-variable model (Model 3) reduced error by 6.5%, (0.214-0.2)/0.214, at the course section level and 12.8%, (0.485-0.423)/0.485, at the instructor level.

Results of Model 4

Building upon Model 3, Model 4 added interactions between the two course format predictors (5-week online and 16-week online) and the six selected predictors (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM). These interactions enabled me to investigate if the effects of the six selected predictors on academic performance varied across the different course formats. It should be noted that to better understand the meaning of each interaction, I conducted separate analyses for each selected predictor, resulting in a total of six separate analyses. Correspondingly, I created six combined models (i.e., one combined model for each selected predictor). See Tables 5.1 to 5.6 for the results of these combined models. In each of the six tables, I only reported the relevant interaction variables and the predictor variables involved with the interaction variables because the coefficients of these predictor variables changed after adding the interaction variables. In other words, the coefficients of the predictor variables not reported in the tables remained the same as those in

Model 3. Table 5.1 presents the results of the combined model for the selected predictor, cumulative GPA.

Table 5.1

Effects of Interactions Between Cumulative GPA and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.850***	0.093	0.669	1.032	2.34
Online16	0.310***	0.069	0.174	0.446	1.363
CGPA	0.443***	0.018	0.408	0.479	1.558
Interaction					
Online5*CGPA	-0.229***	0.033	-0.293	-0.165	0.795
Online16* CGPA	-0.145***	0.022	-0.188	-0.101	0.865

Based on the information in Table 5.1, the effect of cumulative GPA on student academic performance varied significantly across the different course formats. More specifically, the effect of cumulative GPA on academic performance in the 5-week online course format was significantly weaker than the effect of cumulative GPA on academic performance in the traditional course format (-0.229, $p < .001$). Similarly, the effect of cumulative GPA on academic performance in the 16-week online course format was significantly weaker than the effect of cumulative GPA on academic performance in the traditional course format (-0.145, $p < .001$).

Examining the effect of cumulative GPA on academic performance in each course format, I found that it was positive and significant. In other words, in all three course formats, students with higher cumulative GPAs achieved significantly higher academic performance than students with lower cumulative GPAs. The effect of cumulative GPA was strongest in the traditional course format (0.443, $p < .001$). This effect was weaker in both the 5-week online course format (0.443 – 0.229 = 0.214, $p < .001$) and the 16-week online course format (0.443 – 0.145 = 0.298, $p < .001$).

Table 5.2

Effects of Interactions Between Gender and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.492***	0.098	0.299	0.684	1.635
Online16	0.099	0.063	-0.025	0.222	1.104
Female	0.404***	0.048	0.31	0.498	1.497
Interaction					
Online5*Female	-0.176[†]	0.103	-0.377	0.026	0.839
Online16*Female	-0.178**	0.064	-0.304	-0.053	0.837

Based on the information in Table 5.2, the effect of gender (female versus male) on student academic performance varied significantly across the different course formats. More specifically, the discrepancy in academic performance between female and male students in the 5-week online course format was significantly different from the discrepancy in academic performance between female and male students in the traditional course format (-0.176, $p < .10$). Likewise, the discrepancy in academic performance between female and male students in the 16-week online course format was significantly different from the discrepancy in academic performance between female and male students in the traditional course format (-0.178, $p < .01$). Examining the discrepancies individually, in the traditional course format, the log odds of earning a higher grade increased by 0.404 for female students ($p < .001$) when compared to male students, holding all other predictors constant. These log odds were equivalent to a 49.7% increase in the odds of earning a higher grade for female students, compared to male students.

Similar to the traditional course format, in the two online course formats, female students achieved significantly higher academic performance than male students. However, the discrepancy in academic performance between female and male students in either online course format was significantly smaller than the discrepancy in academic performance between female and male students in the traditional course format. In the 5-week online course format, the log odds of earning a higher grade increased by 0.228 (0.404 - 0.176) for female students ($p < .05$) when compared to male students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 25.6%, or 1.256 times, for female students, compared to male students. Similarly, in the 16-week online course format, there was a significant increase in the log odds of earning a higher grade for female students (0.404 – 0.178 = 0.226, $p < .01$) in comparison to male students, holding all other predictors constant. These log odds were equivalent to a 25.4% increase in the odds of earning a higher grade for female students, compared to male students.

Comparing students of the same gender across the different course formats, male students in the 5-week online course format achieved significantly higher academic performance than male students in the traditional course format. In terms of log odds, there was a significant increase in the log odds of receiving a higher grade for male students in the 5-week online course format (0.492, $p < .001$) in comparison to male students in the traditional course format, holding all other predictors constant. These log odds were equivalent to a 63.5% increase in the odds of receiving a higher grade for male students in the 5-week online course format when compared to male students in the traditional course format. Similar results were found for female students. The log odds of receiving a higher grade increased by 0.316 (0.492 – 0.176) for female students in the 5-week online course format ($p < .05$) when compared to female students in the traditional course format, holding all other predictors constant. When converting these log odds to odds, the odds of receiving a higher grade increased by 37.2%, or 1.372 times, for female students in the 5-week online course format, compared to female students in the traditional course format.

Table 5.3

Effects of Interactions Between Age and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.661***	0.164	0.339	0.983	1.937
Online16	0.270*	0.114	0.046	0.494	1.31
Age	0.029***	0.004	0.022	0.036	1.03
Interaction					
Online5*Age	-0.012*	0.006	-0.023	0	0.988
Online16*Age	-0.012**	0.004	-0.021	-0.003	0.988

Based on the information in Table 5.3, the effect of age on student academic performance varied significantly across the different course formats. More precisely, the effect of age on academic performance in the 5-week online course format was significantly weaker than the effect of age on academic performance in the traditional course format (-0.012, $p < .05$). Similarly, the effect of age on academic performance in the 16-week online course format was significantly weaker than the effect of age on academic performance in the traditional course format (-0.012, $p < .01$).

Examining the effect of age on academic performance in each course format, I found that it was positive and significant. In other words, in all three course formats, older students achieved significantly higher academic performance than younger students. The effect of age was strongest in the traditional course format (0.029, $p < .001$). This effect was weaker in both the 5-week online course format (0.029 - 0.012 = 0.017, $p < .05$) and the 16-week online course format (0.029 - 0.012 = 0.017, $p < .01$).

Table 5.4

Effects of Interactions Between Ethnicity and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.23	0.153	-0.069	0.53	1.259
Online16	-0.093	0.1	-0.29	0.103	0.911
NativeHI	-0.637***	0.086	-0.806	-0.468	0.529
Filipino	-0.237**	0.089	-0.411	-0.064	0.789
Black	-0.499**	0.173	-0.838	-0.161	0.607
Hispanic	-0.139	0.173	-0.478	0.2	0.87
Mixed-Race	-0.389***	0.094	-0.573	-0.205	0.678
East Asian	-0.226†	0.119	-0.458	0.007	0.798
Native American	0.198	0.429	-0.642	1.038	1.219
Pacific Islander	-1.132***	0.151	-1.427	-0.836	0.322
Other Asian	-0.334**	0.103	-0.536	-0.133	0.716
Interaction					
Online5*NativeHI	0.318†	0.167	-0.009	0.646	1.375
Online16*NativeHI	0.028	0.109	-0.185	0.241	1.028
Online5*Filipino	-0.145	0.182	-0.501	0.21	0.865
Online16*Filipino	0.091	0.114	-0.133	0.315	1.095
Online5*Black	-0.468	0.339	-1.133	0.197	0.626
Online16*Black	-0.390†	0.222	-0.825	0.046	0.677
Online5*Hispanic	-0.582	0.356	-1.279	0.115	0.559
Online16*Hispanic	-0.346	0.234	-0.804	0.113	0.708
Online5*East Asian	0.808***	0.238	0.342	1.274	2.243
Online16*East Asian	0.539***	0.151	0.243	0.836	1.715

Online5*Native American	-0.818	0.889	-2.561	0.925	0.441
Online16*Native American	-0.626	0.545	-1.695	0.442	0.535
Online5*Pacific Islander	0.134	0.302	-0.458	0.727	1.144
Online16*Pacific Islander	0.185	0.214	-0.234	0.603	1.203
Online5*Other Asian	0.085	0.205	-0.316	0.486	1.089
Online16*Other Asian	0.257†	0.135	-0.007	0.52	1.293
Online5*Mixed-Race	0.24	0.188	-0.128	0.607	1.271
Online16*Mixed-Race	0.104	0.121	-0.132	0.34	1.109

As shown in Table 5.4, several significant interactions were found regarding student ethnicity. To begin with, the discrepancy in academic performance between East Asian and White students in the 5-week online course format was significantly different from the discrepancy in academic performance between East Asian and White students in the traditional course format (0.808, $p < .001$). Likewise, the discrepancy in academic performance between East Asian and White students in the 16-week online course format was significantly different from the discrepancy in academic performance between East Asian and White students in the traditional course format (0.539, $p < .001$). Furthermore, the discrepancy in academic performance between other Asian and White students in the 16-week online course format was significantly smaller than the discrepancy in academic performance between other Asian and White students in the traditional course format (0.257, $p < .10$). Moreover, the discrepancy in academic performance between African American/Black and White students in the 16-week online course format was significantly greater than the discrepancy in academic performance between African American/Black and White students in the traditional course format (-0.390, $p < .10$). Finally, the discrepancy in academic performance between Native Hawaiian and White students in the 5-week online course format was significantly smaller than the discrepancy in academic performance between Native Hawaiian and White students in the traditional course format (0.318, $p < .10$).

Examining each discrepancy that included East Asian students, in the traditional course format, the log odds of earning a higher grade decreased by 0.226 for East Asian students ($p < .10$) when compared to White students, holding all other predictors constant. These log odds were equivalent to a 20.2% decrease in the odds of earning a higher grade for East Asian students, compared to White students. In contrast to the traditional course format, in the 5-week online course format, East Asian students achieved significantly higher academic performance than White students. In the 5-week online course format, there was a significant increase in the log odds of earning a higher grade for East Asian students (-0.226 + 0.808 = 0.582, $p < .05$) when compared to White students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 79%, or 1.790 times, for East Asian students, compared to White students.

Comparing the academic performance of East Asian students across the different course formats, East Asian students in either online course format outperformed East Asian students in the traditional course format. More specifically, the log odds of earning a higher grade increased by 1.038 (0.230 + 0.808) for East Asian students in the 5-week online course format ($p < .001$) when compared to East Asian students in the traditional course format, holding all other predictors constant. When converting these log odds to odds, the odds of earning a higher grade increased by 182.4%, or 2.824 times, for East Asian students in the 5-week online course format, compared to East Asian students in the traditional course format. Similarly, there was a significant increase in the log odds of earning a higher grade for East Asian students in the 16-week online course format (-0.093 + 0.539 = 0.446, $p < .05$) when_ compared to East Asian students in the traditional course format, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 56.2% , or 1.562 times, for East Asian students in the 16-week online course format, compared to East Asian students in the traditional course format.

Comparing the academic performance of Native Hawaiian students across the different course formats, Native Hawaiian students in the 5-week online course format earned significantly higher final grades than Native Hawaiian students in the traditional course format. In terms of log odds, there was a significant increase in the log odds of earning a higher grade for Native Hawaiian students in the 5-week online course format (0.230 + 0.318 = 0.548, $p < .05$) when compared to Native Hawaiian students in the traditional course format, holding all other predictors constant. This result indicated that the odds of earning a higher grade increased by 73%, or 1.730 times, for Native Hawaiian students in the 5-week online course format, compared to Native Hawaiian students in the traditional course format.

Table 5.5

Effects of Interactions Between Enrollment Status and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.176*	0.086	0.007	0.346	1.193
Online16	-0.103†	0.057	-0.214	0.008	0.902
Part-Time	-0.027	0.053	-0.13	0.076	0.974
Interaction					
Online5*Part-Time	0.425***	0.101	0.227	0.624	1.530
Online16*Part-Time	0.250***	0.066	0.120	0.380	1.285

Based on the information in Table 5.5, the effect of enrollment status (part-time versus full-time) on student academic performance varied significantly across the different course formats. To be more specific, the discrepancy in academic performance between part-time and full-time students in the 5-week online course format was significantly different from the discrepancy in academic performance between part-time and full-time students in the traditional course format (0.425, $p < .001$). Along the same lines, the discrepancy in academic performance between part-time and full-time students in the 16-week online course format was significantly different from the discrepancy in academic performance between part-time and full-time students in the traditional course format (0.250, $p < .001$).

Examining the discrepancies individually, in the 5-week online course format, the log odds of earning a higher grade increased by 0.398 (-0.027 + 0.425) for part-time students ($p < .001$) when compared to full-time students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 48.9%, or 1.489 times, for part-time students, compared to full-time students. Similar to the 5-week online course format, in the 16-week online course format, part-time students achieved significantly higher academic performance than full-time students. In terms of log odds, in the 16-week online course format, the log odds of earning a higher grade increased by 0.223 (-0.027 + 0.250) for part-time students ($p < .01$) when compared to full-time students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade increased by 25%, or 1.250 times, for part-time students, compared to full-time students.

Comparing the academic performance of students with the same enrollment status across the different course formats, full-time students in the 5-week online course format outperformed full-time students in the traditional course format. In terms of log odds, holding all other predictors constant, the log odds of earning a higher grade increased by 0.176 for full-time students in the 5-week online course format ($p < .05$) when compared to full-time students in the traditional course format. Similarly, part-time students in the 5-week online course format achieved significantly higher academic performance than part-time students in the traditional course format. In terms of log odds, holding all other predictors constant, the log odds of earning a higher grade increased by 0.601 (0.176 + 0.425) for part-time students in the 5-week online course format ($p < .001$) when compared to part-time students in the traditional course format. These results demonstrated that while the 5-week online course format increased the academic performance of both part-time and full-time students, this increase was significantly greater for part-time students (0.425, $p < .001$).

Table 5.6

Effects of Interactions Between Course Difficulty and Course Formats on Academic Performance

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.439***	0.071	0.299	0.578	1.551
Online16	0.042	0.054	-0.064	0.148	1.043
STEM	-0.266	0.268	-0.803	0.272	0.767
Interaction					
Online5*STEM	-0.373†	0.195	-0.755	0.01	0.689
Online16*STEM	-0.298*	0.133	-0.558	-0.037	0.743

Based on the information in Table 5.6, the effect of course difficulty (STEM versus non-STEM courses) on student academic performance varied significantly across the different course formats. In order to be more concise, I refer to students who took STEM courses as “STEM students” and students who took non-STEM courses as “non-STEM students.” Terminology aside, the discrepancy in academic performance between STEM students and non-STEM students in the 5-week online course format was significantly greater than the discrepancy in academic performance between STEM students and non-STEM students in the traditional course format (-0.373, $p < .10$). Similarly, the discrepancy in academic performance between STEM students and non-STEM students in the 16-week online course format was significantly greater than the discrepancy in academic performance between STEM students and non-STEM students in the traditional course format (-0.298, $p < .05$).

Examining the discrepancies individually, in the 5-week online course format, the log odds of earning a higher grade decreased by 0.639 (-0.266 – 0.373) for STEM students ($p < .10$) when compared to non-STEM students, holding all other predictors constant. This change in the log odds indicated that the odds of earning a higher grade decreased by 47.2%, or 0.528 times, for STEM students, compared to non-STEM students. Likewise, in the 16-week online course format, the log odds of earning a higher grade decreased by 0.564 (-0.266 - 0.298) for STEM students ($p < .10$) when compared to non-STEM students, holding all other predictors constant. These log odds were equal to a 43.1% decrease in the odds of earning a higher grade for STEM students, compared to non-STEM students.

Comparing the academic performance of STEM students across the different course formats, STEM students in the 5-week online course format did not perform differently from STEM students in the traditional course format (0.439 - 0.373 = 0.066, $p \geq .10$). However, non-STEM students in the 5-week online course format achieved significantly higher academic performance than non-STEM students in the traditional course format. In terms of log odds, holding all other predictors constant, the log odds of earning a higher grade increased significantly for non-STEM students in the 5-week online course format (0.439, $p < .001$) when compared to non-STEM students in the traditional course format. When converting these log odds to odds, the odds of earning a higher grade increased by 55.1%, or 1.551 times, for non-STEM students in the 5-week online course format, compared to non-STEM students in the traditional course format.

Results of Student Retention Models

Results of Model 5

Model 5 consisted of two elements. The first element was the grand-mean log odds of student retention across all instructors (see "Instructor Mean" in Table 6). The second element was variance. The results showed that the grand-mean log odds was 1.537 ($p < .001$). Regarding variance, the results indicated that there was significant variability in the log odds of student retention at the course section level (u_{0jk}= 0.187, $p < .001$) and at the instructor level (v_{00} = 0.399, $p < .001$). Taking the suggestions of Hox (2017), these results were interpreted as approximate.

Table 6

Baseline Model for Student Retention

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Instructor Mean	1.537***	0.093	1.351	1.724	4.652
Variances					
Level-1	1				
Level-2	0.187***	0.024	0.145	0.241	
Level-3	0.399***	0.088	0.259	0.616	

Note. Level-1 variance was scaled to 1.00. †$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

Intraclass Correlation Coefficient. The intraclass correlation coefficient (ICC) for each level of Model 5 was calculated. As Model 5 was a binary model with a logit link, the variance at level 1 was approximately 3.29 (Hox, 2017). To begin with, the ICC for level 1 was calculated using $\rho = \sigma^2_{Level\ 1}/(\sigma^2_{Level\ 1} + \sigma^2_{Level\ 2} + \sigma^2_{Level\ 3})$. The results showed that the proportion of variance between students was 3.29/(3.29 + 0.187 + 0.399), or 0.849. Next, the ICC for level 2 was calculated using $\rho = \sigma^2_{Level\ 2}/(\sigma^2_{Level\ 1} + \sigma^2_{Level\ 2} + \sigma^2_{Level\ 3})$. The results showed that the proportion of variance between course sections was 0.187/(3.29 + 0.187 + 0.399), or 0.048. Lastly, the ICC for level 3 was calculated using $\rho = \sigma^2_{Level\ 3}/(\sigma^2_{Level\ 1} + \sigma^2_{Level\ 2} + \sigma^2_{Level\ 3})$. The results demonstrated that the proportion of variance between instructors was 0.399/(3.29 + 0.187 + 0.399), or 0.103. Overall, the Wald test and ICC values indicated that there was enough variability at the course section and instructor levels to justify the use of a three-level model.

Results of Model 6

Building upon Model 5, Model 6 added two course format predictors: the 5-week online course format and the 16-week online course format (notated as "Online5" and "Online16" respectively in Table 7). Regarding the 5-week online predictor, the log odds of being retained increased by 0.268 for students who took courses in the 5-week online format ($p < .001$) when compared to their peers who took courses in the traditional format (i.e., 16-week face-to-face), holding the other predictor constant. This change in the log odds indicated that the odds of being retained increased by 30.7%, or 1.307 times, for students who took courses in the 5-week online format when compared to their peers who took courses in the traditional format. However, concerning the 16-week online predictor, there was no significant difference (-0.055, $p \geq .10$) between the 16-week online course format and the traditional course format in terms of student retention.

Table 7

Course Format Predictors for Student Retention

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Instructor Intercept	1.523***	0.099	1.325	1.722	4.588

Course-Level Predictors					
Course Format					
Online5	0.268***	0.075	0.121	0.415	1.307
Online16	-0.055	0.054	-0.162	0.052	0.946
Variances					
Level-1	1				
Level-2	0.176***	0.024	0.135	0.229	
Level-3	0.407***	0.09	0.264	0.627	

Note. Level-1 variance was scaled to 1.00. †$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

Results of Model 7

Building upon Model 6, Model 7 added student-background and course-difficulty predictors that have been shown to affect student retention. The results of Model 7 are presented in Table 8. Consistent with the results of Model 6, the effect of the 5-week online course format remained significant in Model 7. The log odds of being retained increased by 0.208 for students in the 5-week online course format ($p < .01$) when compared to their peers in the traditional course format (i.e., 16-week face-to-face), holding all other predictors constant**.** This change in the log odds indicated that the odds of being retained increased by 23.2%, or 1.232 times, for students in the 5-week online course format when compared to their peers in the traditional course format.

In contrast to the results of Model 6, after adding the student-background and course-difficulty predictors to Model 7, the effect of the 16-week online course format became statistically significant (-0.192, $p < .001$). The log odds of persistence decreased by 0.192 for students in the 16-week online course format ($p < .001$) when compared to their peers in the traditional course format, holding all other predictors constant. This change in the log odds indicated that the odds of persistence decreased by 17.4%, or 0.826 times, for students in the 16-week online course format when compared to their peers in the traditional course format.

Table 8

Student-Background and Course-Difficulty Predictors for Student Retention

Model Term	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Instructor Intercept	0.834***	0.133	0.571	1.096	2.302
Course-Level Predictors					
Course Format					
Online5	0.208**	0.079	0.053	0.364	1.232
Online16	-0.192***	0.057	-0.304	-0.08	0.826
Course Difficulty					
STEM	-0.259	0.234	-0.728	0.211	0.772
Student-Level Predictors					
Academic					
Remedial Math	-0.350***	0.043	-0.435	-0.266	0.704
Remedial English	-0.291*	0.117	-0.522	-0.061	0.747
CGPA	0.322***	0.014	0.294	0.35	1.38
Demographic					
Age	0.013***	0.003	0.008	0.018	1.013
Female	0.257***	0.04	0.178	0.336	1.293
1stGen	-0.148***	0.044	-0.234	-0.063	0.862
Pell	0.129**	0.042	0.048	0.21	1.138
Part-Time	0.076[†]	0.041	-0.005	0.156	1.078
Ethnicity					
NativeHI	-0.492***	0.067	-0.623	-0.36	0.612
Filipino	-0.093	0.074	-0.239	0.052	0.911
Black	-0.588***	0.128	-0.838	-0.338	0.555
Hispanic	0.156	0.163	-0.163	0.475	1.169
East Asian	0.281**	0.1	0.085	0.477	1.324

Native American	-0.029	0.363	-0.74	0.682	0.972
Pacific Islander	-0.754***	0.124	-0.996	-0.512	0.471
Other Asian	-0.173*	0.085	-0.339	-0.007	0.841
Mixed-Race	-0.203**	0.076	-0.351	-0.055	0.816
Variances					
Level-1	1				
Level-2	0.173***	0.025	0.13	0.23	
Level-3	0.324***	0.074	0.207	0.507	

Note. Level-1 variance was scaled to 1.00. †$p < .10$; *$p < .05$; **$p < .01$; ***$p < .001$.

It is important to note that 14 student-background predictors were found to be significant for student retention in Model 7. However, none of the course-difficulty predictors explored in this study were significant for student retention. As expected, one of the course-difficulty predictors, STEM, negatively affected academic performance and student retention. While this predictor had a significant influence on academic performance, it was not found to be significant for student retention (-0.259, $p \geq .10$). Despite this finding, I decided to keep the STEM predictor in Model 7 in order to show that I considered both student-related and course-related predictors, which have been known to affect student retention in the design of this study. The following sections describe the effects of student-background predictors, more specifically demographic and academic predictors.

Demographic Predictors. With respect to age, older students were more likely to persist than younger students (0.013*,* $p < .001$). In regard to gender, there was a significant increase in the log odds of being retained for female students (0.257, $p < .001$) in comparison to male students, holding all other predictors constant. These log odds were equivalent to a 29.3% increase in the odds of being retained for female students when compared to male students.

Concerning enrollment status, the log odds of persistence increased by 0.076 for part-time students ($p < .10$) when compared to full-time students, holding all other predictors constant. This change in the log odds indicated that the odds of persistence increased by 7.8%, or 1.078 times, for part-time students when compared to full-time students. Regarding Pell Grant eligibility, the log odds of being retained increased by 0.129 for Pell Grant recipients ($p < .01$) when compared to students who did not receive a Pell Grant, holding all other predictors constant. This change in the log odds indicated that the odds of being retained increased by 13.8%, or 1.138 times, for Pell Grant recipients when compared to students who did not receive a Pell Grant.

In regard to ethnicity, there was a significant increase in the log odds of persistence for East Asian students (0.281, $p < .01$) in comparison to White students, holding all other predictors constant. These log odds were equivalent to a 32.4% increase in the odds of persistence for East Asian students when compared to White students. For the following five ethnic groups, there was a significant decrease in the log odds of persistence when compared to White students, holding all other predictors constant: African American/Black students (-0.588, $p < .001$), mixed-race students (-0.203, $p < .01$), Native Hawaiian students (-0.492, $p < .001$), other Asian students (-0.173, $p < .05$), and Pacific Islander students (-0.754, $p < .001$).

Finally, concerning first-generation status, the log odds of being retained were significantly lower for first-generation college students (-0.148, $p < .001$) when compared to college students who were not first generation, holding all other predictors constant. When converting these log odds to odds, the odds of being retained decreased by 13.8%, or 0.862 times, for first-generation college students, compared to college students who were not first generation.

Academic Predictors. Regarding remedial English courses, the log odds of being retained decreased by 0.291 for students who previously took remedial English courses ($p < .05$) when compared to students who did not previously take remedial English courses, holding all other predictors constant. This result indicated that the odds of being retained decreased by 25.3%, or 0.747 times, for students who previously took remedial English courses when compared to students who did not. Similarly, concerning remedial math courses, there was a significant decrease in the log odds of being retained for students who previously took remedial math courses (-0.350, $p < .001$) when compared to students who did not previously take remedial math courses, holding all other predictors constant. These log odds were equivalent to a 29.6% decrease in the odds of being retained for students who previously took remedial math courses when compared to students who did not.

With respect to cumulative GPA, a 1-point increase in a student's cumulative GPA was associated with a 0.322 increase in the log odds of persistence ($p < .001$), holding all other predictors constant. When converting these log odds to odds, a 1-point increase in a student's cumulative GPA was associated with a 38% increase in the odds of persistence, holding all other predictors constant.

Finally, in order to examine the amount of error reduced after adding all the predictors to Model 7, I calculated the PRE at the second and third levels. The results of this study demonstrated that in comparison to the baseline model (Model 5), the all-variable model (Model 7) reduced error by 7.5%, (0.187-0.173)/0.187, at the course section level and 18.8%, (0.399-0.324)/0.399, at the instructor level.

Results of Model 8

Building upon Model 7, Model 8 added interactions between the two course format predictors (5-week online and 16-week online) and the six selected predictors (gender, ethnicity, age, cumulative GPA, enrollment status, and STEM). These interactions enabled me to investigate if the effects of the six selected predictors on student retention varied across the different course formats. It should be noted that to better understand the meaning of each interaction, I conducted separate analyses for each selected predictor, resulting in a total of six separate analyses. Correspondingly, I created six combined models (i.e., one combined model for each selected predictor). See Tables 9.1 to 9.6 for the results of these combined models. In each of the six tables, I only reported the relevant interaction variables and the predictor variables involved with the interaction variables because the coefficients of these predictor variables changed after adding the interaction variables. In other words, the coefficients of the predictor variables not reported in the tables remained the same as those in Model 7. Table 9.1 presents the results of the combined model for the selected predictor, enrollment status.

Table 9.1

Effects of Interactions Between Enrollment Status and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	-0.025	0.109	-0.239	0.189	0.975
Online16	-0.304***	0.067	-0.436	-0.172	0.738
Part-Time	-0.137*	0.07	-0.274	-0.001	0.872
Interaction					
Online5*Part-Time	0.473***	0.136	0.207	0.739	1.604
Online16*Part-Time	0.288***	0.087	0.119	0.458	1.334

Based on the information in Table 9.1, the effect of enrollment status (part-time versus full-time) on student retention significantly varied across the different course formats. More specifically, the discrepancy in student retention between part-time and full-time students in the 5-week online course format was significantly different from the discrepancy in student retention between part-time and full-time students in the traditional course format (0.473, $p < .001$). Similarly, the discrepancy in student retention between part-time and full-time students in the 16-week online course format was significantly different from the discrepancy in student retention between part-time and full-time students in the traditional course format (0.288, $p < .001$).

Examining the discrepancies individually, in the traditional course format, the log odds of persistence decreased by 0.137 for part-time students ($p < .05$) when compared to full-time students, holding all other predictors constant. This change in the log odds indicated that the odds of persistence decreased by 12.8%, or 0.872 times, for part-time students, compared to full-time students. While part-time students were less likely to persist in the traditional course format, the opposite was true for the 5-week online course format. In the 5-week online course format, the log odds of persistence increased by 0.336 (-0.137 + 0.473) for part-time students ($p < .05$) when compared to full-time students, holding all other predictors constant. These log odds were equivalent to a 39.9% increase in the odds of persistence for part-time students, compared to full-time students.

Comparing students with the same enrollment status across the different course formats, full-time students in the 5-week online course format did not perform differently from full-time students in the traditional course format in terms of student retention (-0.025, $p \geq .10$). However, part-time students in the 5-week online course format were more likely to persist than part-time students in the traditional course format. In terms of log odds, holding all other predictors constant, the log odds of persistence increased by 0.448 (-0.025 +

0.473) for part-time students in the 5-week online course format ($p < .05$) when compared to part-time students in the traditional course format. These log odds were equivalent to a 56.5% increase in the odds of persistence for part-time students in the 5-week online course format, compared to part-time students in the traditional course format.

Table 9.2

Effects of Interactions Between Ethnicity and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.427†	0.218	-0.001	0.855	1.532
Online16	-0.185	0.131	-0.442	0.071	0.831
NativeHI	-0.519***	0.116	-0.745	-0.292	0.595
Filipino	0.05	0.124	-0.192	0.293	1.052
Black	-0.381†	0.223	-0.818	0.056	0.683
Hispanic	0.516†	0.284	-0.041	1.073	1.675
East Asian	0.116	0.169	-0.215	0.447	1.123
Native American	0.271	0.654	-1.012	1.553	1.311
Pacific Islander	-0.890***	0.188	-1.258	-0.523	0.41
Other Asian	-0.141	0.141	-0.416	0.135	0.869
Mixed-Race	-0.207	0.128	-0.458	0.043	0.813
Interaction					
Online5*NativeHI	-0.026	0.238	-0.493	0.44	0.974
Online16*NativeHI	0.037	0.144	-0.246	0.319	1.037
Online5*Filipino	-0.675**	0.259	-1.183	-0.168	0.509
Online16*Filipino	-0.147	0.157	-0.454	0.16	0.863
Online5*Black	-0.349	0.463	-1.257	0.559	0.705
Online16*Black	-0.308	0.279	-0.856	0.24	0.735
Online5*Hispanic	-1.582**	0.487	-2.537	-0.626	0.206
Online16*Hispanic	-0.275	0.369	-0.998	0.449	0.76

Online5*East Asian	-0.014	0.344	-0.689	0.661	0.986
Online16*East Asian	0.292	0.216	-0.13	0.715	1.34
Online5*Native American	8.139	69.809	-128.693	144.97	3424.286
Online16*Native American	-0.626	0.793	-2.18	0.929	0.535
Online5*Pacific Islander	-0.029	0.387	-0.787	0.729	0.972
Online16*Pacific Islander	0.323	0.266	-0.199	0.844	1.381
Online5*Other Asian	-0.297	0.292	-0.868	0.275	0.743
Online16*Other Asian	-0.006	0.181	-0.36	0.348	0.994
Online5*Mixed-Race	-0.118	0.269	-0.644	0.409	0.889
Online16*Mixed-Race	0.023	0.162	-0.294	0.341	1.024

As shown in Table 9.2, two significant interactions were found regarding student ethnicity. First, the discrepancy in student retention between Filipino and White students in the 5-week online course format was significantly different from the discrepancy in student retention between Filipino and White students in the traditional course format (-0.675, $p < .01$). Second, the discrepancy in student retention between Hispanic and White students in the 5-week online course format was significantly different from the discrepancy in student retention between Hispanic and White students in the traditional course format (-1.582, $p < .01$).

Comparing students of the same ethnicity across the different course formats, there was no significant difference between the 16-week online and traditional course formats in terms of persistence. This pattern was repeated for all the ethnic groups, except Hispanic and White, when comparing the 5-week online course format to the traditional course format.

Table 9.3

Effects of Interactions Between Cumulative GPA and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.518***	0.109	0.304	0.732	1.678
Online16	-0.006	0.079	-0.161	0.149	0.994
CGPA	0.400***	0.024	0.353	0.447	1.491
Interaction					
Online5*CGPA	-0.179***	0.043	-0.264	-0.094	0.836
Online16*CGPA	-0.099***	0.029	-0.157	-0.042	0.905

Based on the information in Table 9.3, the effect of cumulative GPA on student retention significantly varied across the different course formats. More specifically, the effect of cumulative GPA on student retention in the 5-week online course format was significantly weaker than the effect of cumulative GPA on student retention in the traditional course format (-0.179, $p < .001$). Similarly, the effect of cumulative GPA on student retention in the 16-week online course format was significantly weaker than the effect of cumulative GPA on student retention in the traditional course format (-0.099, $p < .001$).

Examining the effect of cumulative GPA on student retention in each course format, I found that it was positive and significant. In other words, in all three course formats, students with higher cumulative GPAs were more likely to persist than students with lower cumulative GPAs. The effect of cumulative GPA was strongest in the traditional course format (0.400, $p < .001$). This effect was weaker in both the 5-week online course format (0.4 – 0.179 = 0.221, $p < .001$) and the 16-week online course format (0.4 – 0.099 = 0.301, $p < .001$).

Table 9.4

Effects of Interactions Between Age and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	-0.149	0.219	-0.578	0.28	0.862
Online16	-0.192	0.149	-0.483	0.1	0.826
Age	0.011*	0.005	0.001	0.02	1.011
Interaction					
Online5*Age	$0.014^{\dagger}$	0.008	-0.002	0.03	1.014
Online16*Age	0.000	0.006	-0.011	0.012	1.000

As presented in Table 9.4, the effect of age on student retention in the 5-week online course format was significantly different from the effect of age on student retention in the traditional course format (0.014, $p < .10$). Examining the effect of age on student retention in the traditional course format, I found that it was positive and significant (0.011, $p < .05$). In other words, in the traditional course format, older students were more likely to persist than younger students. This pattern was repeated for the 5-week online course format, but the effect of age was stronger (0.011 + 0.014 = 0.025, $p < .01$).

Table 9.5

Effects of Interactions Between Course Difficulty and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.209*	0.084	0.043	0.375	1.233
Online16	-0.173**	0.062	-0.294	-0.051	0.841
STEM	-0.21	0.248	-0.706	0.286	0.811
Interaction					
Online5*STEM	0.031	0.238	-0.436	0.498	1.031
Online16*STEM	-0.124	0.153	-0.424	0.177	0.884

Based on the information in Table 9.5, the effect of course difficulty (STEM versus non-STEM courses) on student retention did not vary across the different course formats. The discrepancy in student retention between STEM students and non-STEM students in the 5-week online course format was not significantly different from the discrepancy in student retention between STEM students and non-STEM students in the traditional course format (0.031, $p \geq .10$). Similarly, the discrepancy in student retention between STEM students and non-STEM students in the 16-week online course format was not significantly different from the discrepancy in student retention between STEM students and non-STEM students in the traditional course format (-0.124, $p \geq .10$). When examining the discrepancies independently, none of them were significant. To be more precise, in each of the three course formats, there was no significant difference in student retention between STEM students and non-STEM students.

Comparing the persistence of STEM students across the different course formats, STEM students in the 5-week online course format did not perform differently from STEM students in the traditional course format (0.209 + 0.031 = 0.24, $p \geq .10$). However, unlike STEM students, non-STEM students in the 5-week online course format were more likely to persist than non-STEM students in the traditional course format. In terms of log odds, compared to non-STEM students in the traditional course format, there was a significant increase in the log odds of persistence for non-STEM students in the 5-week online course format, holding all other predictors constant. These log odds were equivalent to a 23.3% increase in the odds of persistence for non-STEM students in the 5-week online course format when compared to non-STEM students in the traditional course format.

Table 9.6

Effects of Interactions Between Gender and Course Formats on Student Retention

Effect	Coefficient (β)	SE	Lower 95% CI	Upper 95% CI	exp β
Main					
Online5	0.266*	0.122	0.026	0.506	1.305
Online16	-0.136†	0.075	-0.283	0.01	0.873
Female	0.319***	0.065	0.191	0.446	1.375
Interaction					
Online5*Female	-0.099	0.137	-0.367	0.17	0.906
Online16*Female	-0.098	0.084	-0.263	0.068	0.907

Based on the information in Table 9.6, the effect of gender (female versus male) on student retention did not vary across the different course formats. In other words, the discrepancy in student retention between female and male students in either online course format was not significantly different from the discrepancy in student retention between female and male students in the traditional course format. Examining the discrepancies individually, in the traditional course format, the log odds of being retained increased by 0.319 for female students ($p < .001$) when compared to male students, holding all other predictors constant. These log odds were equivalent to a 37.5% increase in the odds of being retained for female students, compared to male students. Similarly, in the 16-week online course format, female students were more likely to persist than male students. In terms of log odds, in the 16-week online course format, there was a significant increase in the log odds of being retained for female students (0.319 – 0.098 = 0.221, $p < .05$) in comparison to male students, holding all other predictors constant. When converting these log odds to odds, the odds of being retained increased by 24.7%, or 1.247 times, for female students, compared to male students.

Comparing students of the same gender across the different course formats, female students in the 5-week online course format did not perform differently from female students in the traditional course format in terms of persistence (0.266 – 0.099 = 0.167, $p \geq .10$). However, male students in the 5-week online course format were more likely to persist than male students in the traditional course format. In terms of log odds, compared to male students in the traditional course format, there was a significant increase in the log odds of being retained for male students in the 5-week online course format (0.266, $p < .05$), holding all other predictors constant. These log odds were equivalent to a 30.5% increase in the odds of being retained for male students in the 5-week online course format when compared to male students in the traditional course format.

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Chapter 6: Discussion

The final chapter begins with a discussion of the following six themes: (a) flexibility deficit, (b) flexibility surplus, (c) female and male perceptions of online challenges, (d) flexibility needs of part-time students, (e) perceived difficulty of STEM and non-STEM courses, and (f) error reduction at the instructor level. Regarding each theme, I discussed the results of this study in light of the conceptual framework of flexibility, the hypotheses I made based on the literature reviewed, or a combination of the framework and my hypotheses. The chapter ends with a discussion of the study's limitations, suggestions for future research, and several implications for practice.

Flexibility Deficit

Based on the literature reviewed regarding the online course format (Atchley et al., 2013; Lyke & Frank, 2012; Nemetz et al., 2017; Xu & Jaggars, 2011), I hypothesized that in this study, the 16-week online course format would produce significantly lower student retention and similar academic performance when compared to the traditional course format (i.e., 16-week face-to-face). This hypothesis was consistent with the results of the current study. The results demonstrated that students in the 16-week online course format were less likely to persist than their peers in the traditional course format. Regarding academic performance, students in the 16-week online course format did not perform differently from their peers in the traditional course format.

Furthermore, based on the literature reviewed regarding how online and face-to-face course formats interacted with student and course characteristics to influence student outcomes (Figlio et al., 2010; Kaupp, 2012; Urtel, 2008; Wladis et al., 2014a; Xu & Jaggars, 2014), I hypothesized that in this study, regardless of student and course characteristics, students in the 16-week online course format would perform more poorly than or similar to their peers in the traditional course format in terms of student retention and academic performance. This hypothesis was consistent with the results of the current study, except for one ethnic group. Out of ten ethnic groups, the only group that did not align with this hypothesis was East Asian students. The results of this study demonstrated that East Asian students in the 16-week online course format achieved significantly higher academic performance when compared to East Asian students in the traditional course format.

The inconsistency between the results of this study and my hypothesis can be explained by how ethnic categories are constructed for Asian students. While previous studies had a single overarching ethnic category for Asian students (Johnson & Mejia, 2014; Xu & Jaggars, 2014), in the current study, I created more refined ethnic categories for Asian students. Taking into account the ethnic diversity of Hawaiʻi, I divided Asian students into three categories: Filipino, East Asian (Chinese, Japanese, and Korean), and other Asian. Without surprise, when I combined these three ethnic groups into one category, the results of this study were consistent with my hypothesis and the literature reviewed (Johnson & Mejia, 2014; Xu & Jaggars, 2014).

In this study, 16-week online courses used the online mode of course delivery. This mode of delivery increased flexibility (Ganesh et al., 2015). More specifically, delivering courses online engendered greater flexibility in terms of place and pace. The 16-week online courses in this study were not bound to a certain place. Furthermore, these courses enabled students to pace themselves more independently as they could access course content anytime before corresponding assessment deadlines. However, in the 16-week online course format, students had to endure challenges for the added flexibility associated with online course delivery. According to Gillett-Swan (2017), the common challenges of online learning include: (a) feeling nervous about using technology, (b) leaving familiar face-to-face learning environments, and (c) feeling isolated as a result of difficulties interacting virtually with classmates and instructors.

Marginal utility can explain why the 16-week online course format failed to enhance student outcomes in this study by describing the relationship between the flexibility and challenges that were introduced by online course delivery. The 16-week online course format increased flexibility, but this increase was not greater than the challenges students had to endure for the increased flexibility associated with delivering courses online.

Flexibility Surplus

Based on two bodies of literature, research on the compressed course format and research on the online course format (Atchley et al., 2013; Carman & Bartsch, 2017; Lyke & Frank, 2012; Nemetz et al., 2017; Sheldon & Durdella, 2009; Walker, 2017; Xu & Jaggars, 2011), I hypothesized that in this study, student outcomes in the 5-week online course format would be similar to or better than those in the traditional course format. Consistent with the hypothesis I formulated regarding the 5-week online course format, the results of this study demonstrated that students in the 5-week online course format outperformed their peers in the traditional course format in terms of student retention and academic performance.

It is essential to highlight that none of the previous studies, which investigated how student and course characteristics interacted with different course formats to influence student outcomes, included the online compressed course format. By addressing this research gap, the current study has made a valuable contribution to the existing scholarly literature on course formats. More specifically, this study bridged the gap by investigating the online compressed course format and its interactions with student and course characteristics.

The results of this study showed that regardless of student and course characteristics, students in the 5-week online course format outperformed or performed as well as students in the traditional course format in terms of student retention and academic performance. These results indicate that the online compressed course format has the potential to improve student outcomes for a variety of learners.

In this study, like the 16-week online course format, the 5-week online course format used-the online mode of course delivery. Therefore, the flexibility and challenges associated with the feature of online course delivery were also present in the 5-week online course format. Flexibility in terms of place remained the same because both course formats were not bound to a specific place. However, flexibility in terms of pace changed in the 5-week online course format. While students in both course formats had the independence to access course content anytime before corresponding assessment deadlines, the shortened duration of the 5-week online format lessened the time students had to access course materials.

In this study, unlike the 16-week online course format, the 5-week online course format had a compressed schedule. This feature of course compression added another layer of flexibility to the 5-week online course format. When the UHCC system offered the same 5-week online course multiple times throughout a 16-week semester, students had the flexibility to take the course when they were less busy. Since students selected more convenient course times at which they were able to prioritize their studies, their non-academic responsibilities were less likely to impede their academic progress. However, in the 5-week online course format, students had to endure challenges for the added flexibility associated with the feature of course compression. Daniel (2000) and Davies (2006) identified three common challenges of compressed courses: a heavier daily course workload due to a shorter semester, mental fatigue, and physical burnout.

Marginal utility can provide a rationale for why the 5-week online course format successfully enhanced student outcomes in this study by describing the relationship between the flexibility and challenges that were introduced by online course delivery and course compression. In the 16-week online course format, the feature of online course delivery did not produce the flexibility needed to overcome the challenges associated with this feature. However, when the online course delivery and course compression features were paired together in the 5-week online course format, they produced enough flexibility to overcome the challenges associated with these two features. Building upon the place and pace flexibility produced by online course delivery, course compression added another layer of flexibility to the 5-week online course format by allowing students to take courses when they were less busy. Altogether, the multiple layers of flexibility in the 5-week online course format surmounted all the challenges students had to endure to benefit from online course delivery and course compression.

Gender and the Perception of Online Challenges

The results of this study demonstrated that female and male students in the 5-week online course format generally outperformed their peers from the same gender group in the traditional course format. However, concerning the performance of male students, the gap between these two course formats was wider than that of female students. The results also showed that female and male students in the 16-week online course format generally underperformed their same-gender peers in the traditional course format. However, concerning the performance of male students, the gap between the two course formats was narrower than that of female students. All these results can be explained by how women and men differently perceive challenges associated with online learning. Previous studies consistently showed that men perceived online learning to be less challenging, compared to women (Celik & Ipcioglu, 2008; Ong & Lai, 2006). For example, Ong and Lai (2006) found that men rated their ability to adapt to computer technology and use online learning tools higher than women. Reflecting on these findings, the challenges associated with online course delivery, especially nervousness about using technology (Gillett-Swan, 2017), had less of an effect on male students in this study. Thus, male students were more likely to adjust to online courses easier than their female peers.

The Need of Part-Time Students: Flexibility Provided by Online Course Formats

Consistent with previous studies (Adelman, 1999; Feldman, 1993; Horn, 1998), the results of this study demonstrated that overall, part-time students underperformed full-time students in the traditional course format. However, in the two online course formats, part-time students generally outperformed full-time students. These results can be explained by how part-time and full-time students differently perceive the flexibility associated with online course formats. The U.S. Department of Education defined part-time students as nontraditional students (Gilardi & Guglielmetti, 2011). According to Crews and Butterfield (2014), nontraditional students valued the flexibility offered by course formats to a significantly greater extent than traditional students. Nontraditional students reported that increased flexibility through the use of online course delivery enabled them to study and work at the same time as well as study where and when they wanted. Reflecting on these previous studies, the flexibility associated with online course delivery had a greater effect on part-time students in this study. Therefore, the overall performance of part-time students increased in the two online course formats. Moreover, this increase was greater in the 5-week online course format.

The flexibility associated with online course delivery was present in the two online course formats of this study. However, the flexibility associated with course compression was only present in the 5-week online course format. Students had the flexibility to take 5-week courses when they were less busy because the UHCC system offered the same 5-week online course multiple times throughout a 16-week semester. As the flexibility of the 5-week online course format was greater than that of the 16-week online course format, part-time students were more likely to persist and achieve higher academic performance in the 5-week online course format.

Perceived Difficulty of STEM and Non-STEM Courses

The results of this study demonstrated that both STEM and non-STEM students in the 16-week online course format generally underperformed their peers who took the same type of courses in the traditional format. However, concerning the performance of STEM students, the gap between the 16-week online and traditional course formats was wider than that of non-STEM students. These results can be explained by the perceived difficulty of STEM courses. From an early age, many American students form the perception that STEM subjects are hard and boring (Roberts et al., 2018). In the current study, STEM and non-STEM students in the 16-week online course format had to endure the challenges associated with online course delivery. On top of these challenges, STEM students also needed to navigate the obstacles related to subject difficulty.

Unlike the 16-week online course format, the results of this study showed that both STEM and non-STEM students in the 5-week online course format generally outperformed their peers who took the same type of courses in the traditional format. However, regarding the performance of non-STEM students, the gap between the 5-week online and traditional course formats was wider than that of STEM students. These results indicated that the 5-week online course format benefitted both STEM and non-STEM students. Nonetheless, the format was comparatively less beneficial to STEM students because they had to endure the challenges associated with subject difficulty.

Error Reduction at the Instructor Level

The results of this study demonstrated that when compared to the baseline model for academic performance (Model 1), the corresponding all-variable model (Model 3) reduced error at both the course section and instructor levels. Similarly, in comparison to the baseline model for student retention (Model 5), the corresponding all-variable model (Model 7) reduced error at both levels.

Considering the absence of instructor-level predictors in this study, the noteworthy reduction in error at the instructor level raised an interesting question. The design of this study and the STEM predictor might answer this question. In this study design, each instructor taught their respective course across all three formats, leading to a confounding of the instructors and courses. More precisely, these instructor-course pairings appeared to delineate between instructors teaching STEM courses and those instructing non-STEM courses. In this study, the STEM predictor was included as a course-level predictor to differentiate STEM courses from non-STEM courses, mirroring previous studies (Wladis et al., 2014b, 2017). However, due to the instructor-course pairings, the STEM predictor seemed to act as not only a course-level predictor but also an instructor-level predictor. This dual functionality, which was a confounding issue, appeared to reduce error at the instructor level even in the absence of explicit instructor-level predictors.

Limitations

I recognize five limitations in regard to this study. The first limitation was the absence of instructor-level predictors. If these predictors were available, I would have included them to improve the explanatory power of the models. Unfortunately, I was unable to access data on instructor demographics and professional attributes, such as age, years of teaching experience, and educational attainment.

Another point regarding the first limitation was how the dual functionality of the STEM predictor partially mitigated this limitation. The STEM predictor was included as a course-level predictor to differentiate STEM courses from non-STEM courses in the current study. However, in addition to acting as a course-level predictor, the STEM predictor also seemed to act as an instructor-level predictor because it delineated between STEM and non-STEM instructors. The dual functionality of the STEM predictor appeared to reduce error at the instructor level, partially mitigating the first limitation.

Second, compared to courses taught in either 16-week format, 5-week online courses were limited in terms of course level, subject, and designation. Since I only included courses taught in all three formats, the variation of the courses used in the current study was limited. If this variation was increased, different findings might have emerged. For example, it is possible that more course-level predictors would have been significant.

Third, this study only included a specific type of compressed course, 5-week online. Compressed courses are not new to two-year and four-year postsecondary institutions (Rudolph, 2021). Since the late 1800s, institutions of higher education have been offering compressed courses in a wide range of lengths. In the information age, technological advancements allowed compressed courses to be taught in the online format. The UHCC system exemplifies this trend by providing 6-week face-to-face, 5-week online, 6-week online, and 8-week online compressed courses. In this study, I chose the 5-week online course format because within the UHCC system, most 6-week online courses were intersession courses, and all 8-week online courses were limited to certain departments.

Regarding the face-to-face compressed course format, 6-week face-to-face courses were not included in this study because within the UHCC system, few courses were taught in this format. If courses in the face-to-face compressed format were included in this study, then the sample size would be drastically reduced as this study requires courses to be taught across all formats under analysis. Carman and Bartsch (2017) as well as Bryant et al. (2003) insisted that face-to-face compressed courses provide more flexibility than regular semester-length face-to-face courses (i.e., 14 to 16 weeks). If the face-to-face compressed course format was included in this study, the comparisons between this format and the other formats would provide a more in-depth understanding of how flexible course formats affect student retention and academic performance.

The fourth limitation was related to assessment practices. In the data used for this study, each instructor taught their respective course in all three formats from spring 2018 to spring 2021. This 3-year study period overlapped with the COVID-19 pandemic. Karadag (2021) stated that higher education instructors tended to grade their students more leniently during the COVID-19 pandemic. Conversely, Panadero et al. (2022) found that within the context of higher education, assessment practices remained largely the same during the COVID-19 pandemic. While student outcomes in this study were generally consistent across the pandemic and non-pandemic periods, I was not able to contact the participating instructors to inquire about pandemic grading practices. Regarding the use of the same assessments across all three formats, the Director of Academic Technologies for the University of Hawai‘i stated that the 5-week online course format was designed to employ the same assessments as the other two course formats (H. Okimoto, personal communication, November 17, 2023). However, I was not able to confirm this information directly with the participating instructors.

Finally, the characteristics used to identify nontraditional students were limited in this study. I only examined the following two characteristics: part-time enrollment status and obtaining a GED instead of a high school diploma. In the data I requested, other identifying characteristics, such as working full time and having children, were not available. Investigating these characteristics could provide a more complete understanding of how nontraditional students perform across different course formats in terms of student retention and academic performance.

Future Research

Future researchers need to consider adding a qualitative component to provide a narrative that helps to explain the quantitative results. For example, future researchers could conduct individual or focus group interviews with students. These interviews may provide insights into why students perform differently across course formats. Future researchers could also conduct classroom observations. These observations may help future researchers understand how instructors adapt course materials and strategies across different course formats.

In future studies, researchers should include instructor-related variables, such as age, years of teaching experience, and educational attainment. These variables can be used as instructor-level predictors to improve the explanatory power of multilevel models, better reflecting current educational practices.

Researchers should also incorporate a wider array of characteristics that identify nontraditional students, such as working full time, into future studies. By investigating interactions between these characteristics and different course formats, future researchers can construct a more complete picture of how nontraditional students perform across course formats.

Moreover, future researchers may use a different measure of student retention, such as graduation. With the aim of doing so, future researchers could conduct a study with three groups of participants: (a) those who previously took face-to-face courses only, (b) those who previously took online courses only, and (c) those who previously took online compressed courses only. Using these participants, future researchers can compare student retention, as measured by graduation rates or enrollment in the subsequent semester, across the different course formats.

Additionally, future researchers can explore different lengths of compressed courses to find a length that maximizes student outcomes. The results of this study demonstrated that among the three course formats, the 5-week online course format produced the highest academic performance and the greatest student retention. Therefore, it is worth it to focus on the online compressed course format. More specifically, future researchers can examine how the degree of course compression influences student retention and academic performance within the context of online learning. For example, a study could compare student outcomes across 5-week, 8-week, and 10-week online courses.

Finally, in follow-up studies, researchers must consider including face-to-face compressed courses. Carman and Bartsch (2017) as well as Bryant et al. (2003) insisted that face-to-face compressed courses provide more flexibility than regular semester-length face-to-face courses (i.e., 14 to 16 weeks). Thus, the comparisons between the face-to-face compressed course format and other course formats are likely to provide a more in-depth understanding of how flexible course formats affect student retention and academic performance.

Implications for Practice

With the exception of one student characteristic, the results of this study demonstrated that regardless of student and course characteristics, students in the 16-week online course format underperformed or did not perform differently from students in the traditional course format in terms of student retention and academic performance. In contrast, students in the 5-week online course format, regardless of student and course characteristics, outperformed or performed as well as students in the traditional course format in terms of student retention and academic performance. The student and course characteristics that increased both student retention and academic performance in the 5-week online course format were (a) part-time enrollment, (b) being male, and (c) taking non-STEM courses. The characteristics that increased either student retention or academic performance in the 5-week online course format were (a) full-time enrollment, (b) being female, (c) being Native Hawaiian, and (d) being East Asian.

Implications When 5-Week Online Courses Outperform Traditional Courses

Concerning enrollment status, the results of this study demonstrated that part-time students in the 5-week online course format were more likely to persist and achieve higher academic performance than part-time students in the traditional course format. The implication that can be derived from these results is that academic advisors at two-year postsecondary institutions should direct part-time students to take 5-week online courses as part-time students are more likely to excel in this course format in terms of academic performance and student retention.

In contrast to part-time students, full-time students in the 5-week online course format did not perform differently from full-time students in the traditional course format in terms of student retention. For academic performance, full-time students in the 5-week online course achieved better outcomes than full-time students in the traditional course format. The implication that can be derived from these results is that academic advisors at two-year postsecondary institutions should encourage full-time students to take 5-week online courses as full-time students are more likely to succeed in this course format in terms of academic performance.

With respect to gender, the results of this study showed that male students in the 5-week online course format outperformed male students in the traditional course format in terms of academic performance and student retention. The results also showed that overall, female students in the 5-week online course format achieved greater success than female students in the traditional course format. More specifically, while female students in the 5-week online course format performed as well as female students in the traditional course format in terms of student retention, female students in the 5-week online course format achieved higher academic performance. The implication that can be derived from these results is that academic advisors at two-year postsecondary institutions should recommend the 5-week online course format to both female and male students.

In regard to students who took non-STEM courses, the results of this study demonstrated that students who took non-STEM courses in the 5-week online format were more likely to persist and achieve higher academic performance than students who took non-STEM courses in the traditional format. The implication that can be inferred from these results is that academic advisors at two-year postsecondary institutions should encourage students to take non-STEM courses in the 5-week online format.

Concerning Native Hawaiian students, the results of this study demonstrated that Native Hawaiian students in the 5-week online course format achieved overall better outcomes than Native Hawaiian students in the traditional course format. More precisely, while Native Hawaiian students in the 5-week online course format performed as well as Native Hawaiian students in the traditional course format in terms of student retention, Native Hawaiian students in the 5-week online course format attained significantly higher academic performance. The implication that can be derived from these results is that academic advisors at two-year postsecondary institutions should direct Native Hawaiian students to take 5-week online courses as Native Hawaiian students are more likely to excel in this course format in terms of academic performance.

As for East Asian students, the results of this study showed that East Asian students saw overall greater benefits from the two online course formats, compared to the traditional course format. More specifically, East Asian students in either online course format achieved significantly higher academic performance than East Asian students in the traditional course format. In terms of student retention, East Asian students in either online course format did not perform differently from East Asian students in the traditional course format. The implication that can be derived from these results is that academic advisors at two-year postsecondary institutions should promote online courses and online compressed courses to East Asian students as they are more likely to excel in these course formats in terms of academic performance.

Thus far, I have discussed the student and course characteristics that increased student retention, academic performance, or both in the 5-week online course format. The implication that can be derived from these results is that 5-week online courses should be recommended to students with these characteristics as the 5-week online course format maximizes the performance of these students.

Implications When 5-Week Online Courses Outperform 16-Week Online Courses

Among the student and course characteristics that produced similar outcomes in the 5-week online and traditional course formats, students who took STEM courses and African American/Black students underperformed in the 16-week online course format. Beginning with students who took STEM courses, there was no significant difference between students who took STEM courses in the 5-week online format and students who took STEM courses in the traditional format in terms of both academic performance and student retention. However, students who took STEM courses in the 16-week online format earned lower final grades and were less likely to persist than students who took STEM courses in the traditional format. The implication that can be derived from these results is that when students at two-year postsecondary institutions need to take online STEM courses, either due to the academic calendar or personal circumstances, academic advisors should direct these students to the 5-week online course format.

Similarly, African American/Black students in the 5-week online course format did not perform differently from African American/Black students in the traditional course format in terms of both academic performance and student retention. However, African American/Black students in the 16-week online course format overall underperformed

African American/Black students in the traditional course format. While there was no significant difference in student retention between the 16-week online and traditional course formats for African American/Black students, African American/Black students in the 16-week online course format earned significantly lower final grades. The implication of these results is that when African American/Black students at two-year postsecondary institutions need to take online courses, either due to the academic calendar or personal circumstances, academic advisors should direct these students to the 5-week online course format.

So far, I have discussed the student and course characteristics that led to similar outcomes in the 5-week online and traditional course formats but led to poor results in the 16-week online course format. For students who took STEM courses and African American/Black students, the 5-week online course format offered greater benefits than the 16-week online course format. This finding has broad implications given that 14- to 16-week courses, regardless of whether they are delivered face-to-face or online, are the dominant course length in higher education (Bostwick et al., 2022). Within the context of online education, the efficiency of the 16-week course length is questionable, especially for students in STEM courses and African American/Black students.

It is important to bolster the performance of students in STEM courses because there is a high demand for STEM professionals (Chen, 2013; Sithole et al., 2017). However, students in STEM courses tend to earn lower final grades and are less likely to persist (Chen, 2013, 2015; Sithole et al., 2017). At least for online courses, the results of this study suggest that compressed courses have the potential to improve student retention and academic performance in STEM education.

It is also essential to assist African American/Black students in enhancing their academic performance. African American/Black students tend to enter college academically underprepared (Davis & Palmer, 2010). Additionally, students of color are more likely to begin their college journey at two-year institutions when compared to White students (National Center for Education Statistics, 2021b). African American/Black students consistently adhere to this pattern; therefore, helping them succeed at two-year postsecondary institutions is imperative. Based on the results of this study, when compared to the 16-week online course format, the 5-week online course format has the potential to enhance the academic performance of African American/Black students.

Conclusion: Considering the Use of 5-Week Online Courses

In conclusion, this study has shown that the 5-week online course format benefitted the following three groups the most: (a) part-time students, (b) male students, and (c) non-STEM students. These three groups were more likely to persist and achieve higher academic performance in the 5-week online course format. However, it is crucial for educators and administrators to recognize that the remaining groups of students did not underperform in the 5-week online course format. Therefore, two-year postsecondary institutions should offer a variety of 5-week online courses across levels, subjects, and designations. Moreover, by carefully planning and designing 5-week online courses to maintain the necessary rigor, two-year postsecondary institutions can consider transitioning their 16-week online courses to 5-week online courses.

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