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PREFACE

This issue features two studies that offer insights for institutional researchers examining student success, from first-year retention to post-graduation employment. Both use campus-level data to identify patterns in student outcomes, providing practical examples of how institutions can leverage their own data to inform advising, programming, and policy.

In *The Relationship between High-Risk Courses and Retention in University*, Chen Zong and Suzann M. Koller explore how first-year enrollment in high-risk courses affects second-year retention among first-time, full-time students. Drawing on data from a large public research university, the authors identify key predictors of retention—including first-semester GPA, high school GPA, major declaration, first-generation status, and the number of high-risk courses attempted. Their findings show a statistically significant negative relationship between the number of high-risk courses and the likelihood of retention. Although the study does not account for potential endogeneity—such as unmeasured student characteristics that might influence both course selection and persistence—it offers a descriptive profile of students most affected by academic risk. This study underscores the value of monitoring high-risk course enrollment early in a student's academic path and emphasizes the role of proactive advising and course planning in supporting retention.

In *Did They Get What They Came For?*, Cassandra R. Kepple, Samantha Nix, Andrew Brady, and Jeckson de Andrade Silva explore the relationship between work-integrated learning (WIL) and employment outcomes for recent graduates. Drawing on graduation survey responses collected over seven years at a large public research university, the authors examine how participation in experiential learning opportunities—such as internships, co-ops, and practica—correlates with securing a job offer upon graduation. Importantly, they trace how this relationship shifted during the COVID-19 pandemic and assess variation by student background, including first-generation status, Pell Grant eligibility, and underrepresented minority status. While future work might benefit from disaggregating by field of study or internship type, the authors provide a compelling starting point for understanding how real-world experiences shape student transitions to the workforce.

Together, these studies show how both academic experiences in the classroom and hands-on learning outside the classroom shape student success. They provide helpful guidance for colleges and universities working to improve retention and support students as they move from college into their careers.

Iryna Muse
Editor

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The Relationship between High-Risk Courses and Retention in University

Chen Zong and Suzann M. Koller

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Abstract

Understanding the relationship between high-risk courses and Fall-to-Fall retention is essential to enhance student persistence and academic achievement in higher education institutions. The purpose of this study is to examine the relationship between high-risk courses and Fall-to-Fall retention of first-time, full-time students. The course data of 8,220 students between 2016 and 2020 at a large public research university were analyzed using descriptive statistics, correlation, and logistic regression methods: First, the characteristics of high-risk courses and the students who took the most high-risk courses were identified. Second, the findings of correlation analysis indicate that there was a statistically significant correlation between Fall-to-Fall retention and the number of high-risk courses students take in their first year. Third, the significant predictors of retention include the following: first-semester GPA, high school GPA, tuition residency, total number of courses taken in their first year, whether the student is first-generation, whether the student has an undeclared major, and the number of high-risk courses the student takes in their first year. The results of model likelihood ratio test indicate that the final model provides a significantly better fit to the data than the null model (χ^2 = 2393.9, *df* = 7, $p < .001$, R^2 = 39.9%). The findings of this study will provide useful information that institutions can use to identify the high-risk courses and to increase retention rate.

Keywords: high-risk courses, retention, higher education, logistic regression

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INTRODUCTION

In higher education institutions, high-risk courses can be a challenge for students, faculty, and administrators. These courses, distinguished by their demanding curriculums and elevated difficulty levels, can impact academic performance, retention rates, and overall student success (Martin & Arendale, 1992). In this study, the high-risk course is defined as a course with a low percentage of students who pass (i.e., including courses where students earn letter grades A, B, C, or D), which is slightly different from high DFW rate courses (i.e., including courses where students earn grades D, F, or Withdrawal) or high-failure rate courses (i.e., including courses where students earn grade F only).

Fall-to-Fall retention rates (i.e., the percentage of students who persist from one academic year to the next) serve as a vital indicator of student success and institutional effectiveness in higher education. Because retention rates in higher education institutions are usually focused on the first-year to second-year performances when there are no data about first-year students' previous college-level course work, it is difficult to identify and provide supports to high-risk students (Martin & Arendale, 1992). Therefore, understanding the factors contributing to the risk associated with the first-year, high-risk courses is essential for educators and administrators to develop effective strategies to support first-time, first-year students; and understanding the relationship between high-risk courses and Fall-to-Fall retention is essential to enhance student persistence and academic achievement.

The purpose of this study is to examine the relationship between high-risk courses and Fall-to-Fall retention of the first-time, full-time students at a large public research university. In this study, a first-time, full-time student is defined as a student who has no prior postsecondary education experience attending any institution for the first time at the undergraduate level, who is enrolled for 12 more semester credits (Integrated Postsecondary Education Data System [IPEDS], 2025). A high-risk course is defined as a first-year, for-credit course with 50 or more first-time, full-time students enrolled during the 5 years between Fall 2016 and Fall 2020, with fewer than 80% of the enrolled students passing the course. The findings of this study will provide useful information to identify the high-risk courses, improve the student success in these courses, and increase the Fall-to-Fall retention rate. There were three research questions:

- RQ1: What are the average number of high-risk courses that students take in their first year, by student characteristics and retention status?
- RQ2: Is there a statistically significant association between high-risk courses and Fall-to-Fall retention?
- RQ3: How well does a combination of student demographics, high school academic background, university academic experience, and first-year course enrollments predict Fall-to-Fall retention?

LITERATURE REVIEWS

To answer the research questions, this literature review explores the characteristics of high-risk courses for college students, the types of students who are most likely to take high-risk courses, the association between high-risk courses and college student retention, and predictive models for college student retention, with a focus on the inclusion of high-risk courses.

Characteristics of High-Risk Courses

The academic success of first-time, full-time students is a critical focus for higher education institutions. High-risk courses, often characterized by high failure rates and significant academic challenges, can impact students' academic success and retention at the institution. Identifying these courses and understanding their characteristics can help institutions implement strategies to improve student retention and success. High-risk courses "include those that have the following characteristics: large amounts of weekly readings from both difficult textbooks and secondary library reference works, infrequent examinations that focus on higher cognitive levels of Bloom's taxonomy, voluntary and unrecorded class attendance, and large classes in which each student has little opportunity for interaction with the professor or the other students" (Martin & Arendale, 1992, p. 14).

STEM (science, technology, engineering, and mathematics) courses, online courses, remedial courses, and gateway courses have often been considered to be high-risk courses in previous studies. STEM courses such as computer science, biology, and chemistry are frequently identified as high risk due to the difficulty or rigor of the course; however, non-STEM courses, including public speaking, critical reading, and writing, can also be high risk (Daniel, 2022). Bambara et al.'s (2009) study found that students who were enrolled in online high-risk courses, with over 30% withdrawal and failure rates, often had the academic experience of isolation, challenge, ownership, and acquiescence as the structural themes; the researchers suggested that there was a need for future research examining how other factors affect student retention and positive completion in high-risk courses. Remedial coursework was designed to help students who are not adequately prepared to succeed in college-level courses (Sanabria et al., 2020). Sanabria et al. (2020) found that students who took and passed remedial coursework were more likely to graduate, compared to peers who did not take remedial coursework, while students who did not pass remedial coursework were less likely to obtain a bachelor's degree or took longer than their peers to graduate. Although gateway courses are often considered to be high risk, Sargent et al.'s (2022) study indicated that receiving a DFW grade (i.e., a grade of D, F, or Withdrawal) in a gateway course did not significantly impact graduation rates over a 36-semester study period involving 3,667 students.

Students in High-Risk Courses

High-risk courses present significant challenges to student success in higher education. Understanding the characteristics of college students who are most likely to take high-risk courses is crucial for developing targeted interventions to support at-risk students and to improve their academic success. Daniel (2022) found that students who met developmental course requirement criteria due to poorer academic performance were less likely to retain or persist; they emphasized the importance of enrolling high-risk students in skill-appropriate courses during their first semester to improve long-term retention. Salazar-Fernandez et al. (2021) analyzed how educational trajectories of undergraduate students in high-failure rate courses can lead to late dropouts. Their study suggested that institutions should monitor high-failure rate courses that students enroll in after a stopout, because students who took a stopout while having high-risk courses they must retake were more likely to have a late dropout. Haynes Stewart et al.'s (2011) study indicated that age, gender, high school performance, registration status (full time or part time), and participation in a first-year orientation program significantly predicted course outcome (pass or fail).

Predictors for Student Retention

Predictive models for college student retention are useful tools for higher education institutions aiming to improve student success. These models typically use a combination of academic, demographic, and behavioral data to predict student outcomes. According to Paterson and Guerrero (2023), logistic regression is one of the commonly used techniques in these models; it allows institutions to identify significant factors that influence student success such as demographics, GPA, and course performance.

Predictive models for college student retention that include high-risk courses can provide valuable insights for higher education institutions. Daniel (2022) emphasized that early success in high-risk courses was a key factor in student resilience and retention, and that identifying and supporting students in these courses could significantly improve their chances of persistence. Higgs et al. (2021) highlighted that course-specific data (e.g., types of activities required in the courses, hours spent studying, teaching methods) could be important indicators for students' performance, retention, and passing rates.

Although it is a common problem in higher education, course failure or high-risk courses receive relatively little research attention (Haynes Stewart et al., 2011). Many previous research studies focused on high-risk students rather than on high-risk courses (Martin & Arendale, 1992). When searching for the keywords "high risk courses" and "retention" on Google Scholar, almost all top results are related to at-risk/high-risk students instead of high-risk courses (e.g., Daniel, 2022; Laskey & Hetzel, 2011; Valentine et al., 2011), and only a few studies explored college students enrolled in high-risk courses (e.g., Bambara et al., 2009; Martin & Arendale, 1992). Some studies analyzed the relationship between course failure and graduation or degree completion instead of between course failure and retention rates (e.g., Sanabria et al., 2020; Sargent et al., 2022). Some studies focused only on instructional approaches to improve course performance but did not analyze the relation between high-risk courses and retention (e.g., Martin & Arendale, 1992; Stone & Jacobs, 2008). Most studies focused on only one type of high-risk course; for example, some studies focused on online or distance learning courses (Baker et al., 2015; Bambara et al., 2009; Nash, 2005; Simpson, 2013), gateway courses (Bloemer et al., 2017; Sargent et al. 2022), remedial courses (Gajewski & Mather, 2015; Sanabria et al., 2020), or only one specific course such as calculus (Norton et al., 2018), geology (Roberts et al. 2018), or psychology (Haynes Stewart et al., 2011). Therefore, the research findings of this study will fill the gap in current literature with useful information about the relationship between high-risk courses and retention, with the goal of improving student success in higher education institutions.

METHODS

This study used 5 years of data of first-time, full-time students enrolled in a public research university located in a town in the United States. Overall, the average total enrollment of the institution was around 10,000 to 12,000, including both undergraduate and graduate academic programs, with a student-to-faculty ratio of 13:1. In addition, first-time, full-time student enrollments were between 1,400 and 1,800 for each Fall cohort. The overall Fall-to-Fall retention rate of first-time, full-time students has ranged from 75% to 79% for the past 5 years. Using descriptive statistics, correlation, and logistic regression methods, the students' course and retention data were analyzed to explore the research questions.

Data Source and Sample

The data of first-time, full-time students (8,220 students) enrolled in Fall semesters between 2016 and 2020 were used in this study. The students' demographic information is presented in Table 1. About 77% of the first-time, full-time students between Fall 2016 and Fall 2020 were White (n = 6,355); the balance (23%) represented the other Race/Ethnicity groups, including Race and Ethnicity unknown (*n* = 564), Hispanics of Any Race (*n* = 557), Two or More Races (*n* = 372), Nonresident Alien (*n* = 114), Black or African American (*n* = 111), Asian (*n* = 95), American Indian or Alaska Native (*n* = 42), and Native Hawaiian or Other Pacific Islander (*n* = 10). About the same numbers of Female (*n* = 4,128) and Male (*n* = 4,092) students were represented in this sample. Most of the students in this sample were aged 19 and younger (*n* = 7,976); there were 217 students were aged 20–24, and only 27 students were aged 25 and older. About 24% of the students in this sample were first-generation college students (*n* = 1,941); the balance (76%) were not first-generation college students (*n* = 6,279). Finally, the number of in-state students (*n* = 4,283) was slightly higher than out-of-state students (*n* = 3,937) in this study.

Table 1. Demographic Information of First-time, Full-time Students between Fall 2016 and Fall 2020

Student Characteristics	Total	
Race/Ethnicity	**#**	**%**
American Indian or Alaska Native	42	1%
Asian	95	1%
Black or African American	111	1%
Hispanics of Any Race	557	7%
Native Hawaiian or Other Pacific Islander	10	0%
Nonresident Alien	114	1%
Race and Ethnicity unknown	564	7%
Two or More Races	372	5%
White	6,355	77%
Gender		
Female	4,128	50%
Male	4,092	50%
Age at Entry		
19 and under	7,976	97%
20–24	217	3%
25+	27	0%
First-Generation Status*		
First-Generation	1,941	24%
Not First-Generation	6,279	76%
Tuition Residency		
In-State	4,283	52%
Out-of-State	3,937	48%
Total	**8,220**	**100%**

Note: *First-generation status is based on answers to the question: "Do either of your parents have a 4-year baccalaureate degree?"

High-Risk Courses

There were 77,455 undergraduate-level, for-credit course records that the 8,220 first-time, full-time students took in their first year at the university. There were 21 courses identified as high risk for first-time, full-time students using these criteria (Table 2):

- Undergraduate level courses only
- First-year courses only
- Credit courses only (attempted credit > 0)
- 5 years' total enrollment > = 50
- Pass rate < 80%

Table 2. High-Risk First-Year Courses for First-Time, Full-Time Students

Course Name	Pass		Fail		Incomplete		Withdraw		Total
	#	%	#	%	#	%	#	%	#
General Biology	2,145	79.6%	310	11.5%	2	0.1%	239	8.9%	2,696
College Algebra	1,191	77.1%	176	11.4%	2	0.1%	175	11.3%	1,544
Trigonometry	618	78.5%	65	8.3%	4	0.5%	100	12.7%	787
Pre-college: Algebra II	378	66.8%	125	22.1%	1	0.2%	62	11.0%	566
Business Calculus	420	79.7%	48	9.1%	0	0.0%	59	11.2%	527
Problem Solving	281	73.2%	39	10.2%	0	0.0%	64	16.7%	384
Intro Computer Science I	293	77.5%	44	11.6%	0	0.0%	41	10.8%	378
Pre-college: Algebra I	277	79.6%	49	14.1%	0	0.0%	22	6.3%	348
Academic Success Skills*	170	60.5%	73	26.0%	1	0.4%	37	13.2%	281
U.S. From 1865	204	78.8%	31	12.0%	0	0.0%	24	9.3%	259
Introduction to Philosophy	190	74.8%	34	13.4%	1	0.4%	29	11.4%	254
Sports Economics	101	78.9%	15	11.7%	0	0.0%	12	9.4%	128
Intro to American Studies	80	75.5%	10	9.4%	5	4.7%	11	10.4%	106
Insect Biology	73	77.7%	8	8.5%	0	0.0%	13	13.8%	94
Pre-college: Pre-Algebra	73	77.7%	10	10.6%	0	0.0%	11	11.7%	94
World Archaeology	62	77.5%	11	13.8%	1	1.3%	6	7.5%	80
Problems in: Electrical and Computer Engineering	57	77.0%	11	14.9%	0	0.0%	6	8.1%	74
Spec. Topics: Build the Future	54	75.0%	0	0.0%	10	13.9%	8	11.1%	72
1st Yr German I	54	77.1%	6	8.6%	1	1.4%	9	12.9%	70
Class Piano II	49	76.6%	6	9.4%	0	0.0%	9	14.1%	64
1st Year Japanese I	39	69.6%	10	17.9%	0	0.0%	7	12.5%	56

Note: * Probation course. Pass includes A, B, C, D, and Satisfied; Fail includes F and Unsatisfied.

The characteristics of 77,455 course records were analyzed using descriptive statistics. Table 3 compares the high-risk courses (pass rate < 80%) and other courses (pass rate > = 80%) based on the course characteristics. Overall, in the 77,455 course records, there were 8,862 records of high-risk courses (11.4%), and 68,593 records of other courses (88.6%).

Table 3. Characteristics of High-Risk Courses

	High-Risk Course		Other Courses		Total
Course Characteristics	#	%	#	#	#
Delivery Method					
Face-to-Face	7,711	12.1%	56,078	87.9%	63,789
Hybrid	72	67.3%	35	32.7%	107
Online	1,036	7.7%	12,373	92.3%	13,409
Unknown	43	28.7%	107	71.3%	150
Core Course*					
Yes	6,985	12.6%	48,567	87.4%	55,552
Communication 1	0	0.0%	4,731	100.0%	4,731
Communication 2	0	0.0%	3,894	100.0%	3,894
Communication 3	0	0.0%	18	100.0%	18
First Year Seminar	0	0.0%	8,105	100.0%	8,105
Human Culture	694	4.7%	14,014	95.3%	14,708
Physical and Natural World	2,790	24.6%	8,546	75.4%	11,336
Quantitative Reasoning	3,242	40.4%	4,783	59.6%	8,025
U.S. and State Constitutions	259	5.5%	4,476	94.5%	4,735
No	1,877	8.6%	20,026	91.4%	21,903
Math or English Gateway**					
English Gateway	0	0.0%	4,676	100.0%	4,676
Math Gateway	3,242	38.9%	5,099	61.1%	8,341
Not Gateway	5,620	8.7%	58,818	91.3%	64,438
Grand Total	**8,862**	**11.4%**	**68,593**	**88.6%**	**77,455**

Note: *Core courses refer to the general education (University Studies Program) courses in this study. ** Math or English Gateway courses are the first course for any program to fulfill the single-course college-level math or English requirement.

Regarding course delivery methods, 67.3% of the 107 hybrid course records and 12.1% of the 63,789 face-to-face course records were identified as a high-risk course. Only 7.7% of the 13,409 online course records were identified as high-risk courses.

Core courses are more likely to be high risk: 12.6% of the 55,552 core course records were identified as high risk, compared to 8.6% of the 21,903 non-core course records. Core courses were identified as courses that meet the general education requirements. Among the eight types of core courses, 40.4% of the 8,025 Quantitative Reasoning core course records and 24.6% of the 11,336 Physical and Natural World core course records were high risk, numbers that are much higher than any other types of core courses including Communication 1–3 (0%), First-Year Seminar (0%), Human Culture (4.7%), and U.S. and State Constitutions (5.5%).

Comparing the high-risk percentages of math and English gateway courses, 38.9% of the 8,341 math gateway course records were identified as a high-risk course, and none of the 4,676 English gateway course records was identified as a high-risk course. Of the 64,438 other non-gateway course records, 8.7% were identified as a high-risk course.

Data Analysis and Variables

To answer the first research question, the course data and retention data of the 8,220 first-time, full-time students were analyzed using descriptive statistics (e.g., mean, percentage). To answer the second research question, bivariate correlation analyses were conducted using R to investigate if there was a statistically significant association between Fall-to-Fall retention and the selected student characteristics, including how many high-risk courses students take. To answer the third research question, binary logistic regression was conducted using R to investigate the best predictive model of Fall-to-Fall retention. The method of model selection is used to simplify the logistic regression model by removing variables (Dey et al., 2025; Starbuck, 2023). This approach can enhance the model's interpretability and performance by eliminating irrelevant or redundant predictors. Backward elimination is a common method that starts with the full model and iteratively removes the least significant variables based on a chosen criterion, such as the *p*-value (Starbuck, 2023). This method helps in identifying the most impactful variables while discarding those that do not contribute significantly to the model's predictive power (Dey et al., 2025).

The dependent (outcome) variable was Fall-to-Fall retention, and 13 independent (predictor) variables were selected based on literature reviews for the base model (Bass & Ballard, 2012; DeNicco et al., 2015; Djulovic & Li, 2013; Johnson et al., 2022; Ram et al., 2015):

- **Fall-to-Fall retention:** whether a first-time, full-time student retained after 1 year (retained = 1, not retained = 0)
- **Student demographics:** gender (M = 1, F = 0), age at entry, race/ethnicity (White = 1, minority = 0), first-generation (first-gen = 1, non-first-gen = 0), tuition residency (resident = 1, non-resident = 0)
- **High school academic background:** high school GPA, test score (ACT and SAT converted to ACT scale)
- **University academic experience:** student classification (freshman = 1, sophomore = 2, junior = 3, senior = 4), undeclared major (undeclared = 1, major declared = 0), first-semester GPA, on-campus or distance education (on-campus = 1, distance = 0)
- **First-year course enrollment:** total number of courses taken in their first year, number of high-risk courses taken in their first year.

Data issues were checked before the statistical analyses. The outliers due to data entry errors were removed: (a) a student with an age of 0, (b) a student with a high school GPA of 0, and (c) a student with a high school GPA of 4.15, which exceeds the maximum of 4.0 based on the university policy. The intercorrelations of all the independent variables were tested and no multicollinearity issue ($r > 0.8$) was found between any of them.

FINDINGS

This section will discuss the findings for each of the three research questions. The characteristics of students who took the most high-risk courses were identified. The correlation between students' Fall-to-Fall retention and the number of high-risk courses they took in their first year was investigated, and the other significant predictors associated with retention were explored.

RQ1: What are the average number of high-risk courses that students take in their first year, by student characteristics and retention status?

To answer RQ1, the total number of high-risk courses that each student had taken in their first year was computed, then the means of all students' first-year high-risk courses were computed and compared based on race/ethnicity, gender, age at entry, first-generation status, tuition residency, and Fall-to-Fall retention (Table 4). Overall, the average number of high-risk courses that all 8,220 students took in their first year was 1.08 courses; students who did not retain after 1 year (1.17, n = 1,853) took more high-risk courses than those who retained (1.05, n = 6,367).

Table 4. Average Number of High-Risk Courses in First Year by Student Characteristics and Retention Status

	Retained after 1 Year			Not Retained after 1 Year			Total	
Student Characteristics	Average # high-risk courses	Headcount	% of total	Average # high-risk courses	Headcount	% of total	Average # high-risk courses	Headcount
Race/Ethnicity								
American Indian or Alaska Native	1.36	22	52.4%	1.40	20	47.6%	1.38	42
Asian	1.16	69	72.6%	1.04	26	27.4%	1.13	95
Black or African American	1.25	85	76.6%	1.08	26	23.4%	1.21	111
Hispanics of Any Race	1.18	418	75.0%	1.42	139	25.0%	1.24	557
Native Hawaiian or Other Pacific Islander	1.14	7	70.0%	1.67	3	30.0%	1.30	10
Nonresident Alien	0.97	92	80.7%	0.95	22	19.3%	0.96	114
Race and Ethnicity unknown	1.18	392	69.5%	1.23	172	30.5%	1.19	564
Two or More Races	1.01	268	72.0%	0.99	104	28.0%	1.00	372
White	1.03	5,014	78.9%	1.16	1,341	21.1%	1.06	6,355
Gender								
Female	1.05	3,352	81.2%	1.20	776	18.8%	1.08	4,128
Male	1.05	3,015	73.7%	1.15	1,077	26.3%	1.08	4,092
Age at Entry								
19 and under	1.04	6,198	77.7%	1.18	1,778	22.3%	1.07	7,976
20–24	1.27	152	70.0%	0.97	65	30.0%	1.18	217
25+	1.76	17	63.0%	1.50	10	37.0%	1.67	27
First-Generation Status								
First-Generation	1.12	1,351	69.6%	1.24	590	30.4%	1.16	1,941
Not First-Generation	1.03	5,016	79.9%	1.14	1,263	20.1%	1.06	6,279
Tuition Residency								
In-State	1.04	3,405	79.5%	1.18	878	20.5%	1.07	4,283
Out-of-State	1.07	2,962	75.2%	1.17	975	24.8%	1.09	3,937
Grand Total	**1.05**	**6,367**	**77.5%**	**1.17**	**1,853**	**22.5%**	**1.08**	**8,220**

RACE/ETHNICITY

The results show that American Indian or Alaska Native, Hispanics of Any Race, Native Hawaiian or Other Pacific Islander, White, and students with Race and Ethnicity unknown who did not retain took more high-risk courses than those who retained. American Indian or Alaska Native students had the highest average number of high-risk courses in their first year (1.38, *n* = 42) compared to any other race/ethnicity group. American Indian or Alaska Native students who did not retain after 1 year (1.40, *n* = 20) had a higher average number of high-risk courses than their peers who retained (1.36, *n* = 22). The Fall-to-Fall retention rate of American Indian or Alaska Native students (52.4%, *n* = 22) was also the lowest among all race/ethnicity groups. However, students who identified as Asian, Black or African American, Nonresident Alien, and Two or More Races who did not retain took fewer risk courses than those who retained.

GENDER

Male and female students had the same average number of high-risk courses in their first year (1.08, female *n* = 4,128, male *n* = 4,092). For the students who retained after 1 year, male and female students also had the same average number of high-risk courses (1.05, female *n* = 3,352, male *n* = 3,015). For the students who did not retain after 1 year, both male (1.15, *n* = 1,077) and female students (1.20, *n* = 776) had higher average numbers of high-risk courses than those who retained.

AGE AT ENTRY

Students aged 25 and older had the highest average number of high-risk courses (1.67, *n* = 27) compared to all other age groups, but the sample size of this group was small. Surprisingly, for students aged 25 and older, those who retained after 1 year had a higher average number of high-risk courses (1.76, *n* = 17) than those who did not retain (1.50, *n* = 10). The Fall-to-Fall retention rate of age 25 and older group (63.0%, *n* = 17) was the lowest among all age groups. Students aged 19 and under had the lowest average number of high-risk courses (1.07, *n* = 7,976) and highest retention rate (77.7%, *n* = 6,198).

FIRST-GENERATION STATUS

First-generation students (1.16, *n* = 1,941) took more high-risk courses in their first year than the other students (1.06, *n* = 6,279) on average. Furthermore, first-generation students had a lower retention rate (69.6%, *n* = 1,351) than the other students (79.9%, *n* = 5,016). First-generation students who did not retain after 1 year (1.24, *n* = 590) also had a higher average number of high-risk courses than those who retained (1.12, *n* = 1,351).

TUITION RESIDENCY

Out-of-state students (1.09, *n* = 3,937) had a slightly higher average number of high-risk courses than in-state students (1.07, *n* = 4,283), and out-of-state students (75.2%, *n* = 2,962) also had lower retention rate than in-state students (79.5%, *n* = 3,405). In-state students who did not retain (1.18, *n* = 878) had a higher average number of high-risk courses than those who retained (1.04, *n* = 3,405). Again, out-of-state students who did not retain (1.17, *n* = 975) had a higher average number of high-risk courses than their peers who retained (1.07, *n* = 2,962).

RQ2: Is there a statistically significant association between high-risk courses and Fall-to-Fall retention?

A descriptive analysis was conducted to compare the retention rates by the total number of high-risk courses taken in their first year. Table 5 shows that the students who took three or more high-risk courses had the lowest Fall-to-Fall retention rate (72.2%). The students who took one or two high-risk courses had higher retention rates. The students who did not take any high-risk courses had the highest retention rate (79.4%).

Table 5. Comparison of Retention Rates by Total Number of High-Risk Courses Taken in Their First Year

	Retained after 1 Year		Not Retained after 1 Year		Total
# of high-risk courses	#	%	#	%	#
0	2,087	79.4%	543	20.6%	2,630
1	2,503	77.5%	728	22.5%	3,231
2	1,258	76.7%	382	23.3%	1,640
3+	519	72.2%	200	27.8%	719
Grand Total	**6,367**	**77.5%**	**1,853**	**22.5%**	**8,220**

To address both RQ2 and RQ3, a correlation matrix was computed to examine the intercorrelations (i.e., bivariate/one-to-one correlation) of Fall-to-Fall retention and all the 13 selected independent variables of student characteristics, including the total number of high-risk courses taken in their first year. Table 6 shows that all 13 selected independent variables were significantly correlated with the dependent variable of Fall-to-Fall retention.

Table 6. Intercorrelations for Student Characteristics Variables and Fall-to-Fall Retention

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
		Fall-to-Fall Retention	Gender	Age	Race/ Ethnicity	First-Generation Status	Tuition Residency	HS GPA	ACT & SAT	Student Classification	Undeclared Major	1st Sem GPA	On-Campus	Total Courses Y1	Risk Total Y1
1	Fall-to-Fall Retention	1													
2	Gender	–0.09***	1												
3	Age	–0.04***	0.12***	1											
4	Race/Ethnicity	0.05***	–0.03*	0.02	1										
5	First-Generation Status	–0.11***	–0.02*	0.03*	–0.12***	1									
6	Tuition Residency	0.05***	–0.02*	0.06***	0.03*	0.11***	1								
7	HS GPA	0.30***	–0.22***	–0.09***	0.16***	–0.11***	0.18***	1							
8	ACT & SAT	0.18***	0.01	–0.05***	0.15***	–0.18***	0.05***	0.50***	1						
9	Student Classification	0.07***	–0.06***	–0.01	0.03*	–0.03**	0.06***	0.21***	0.23***	1					
10	Undeclared Major	–0.03**	–0.06***	0.01	–0.02	–0.02	0.05***	–0.08***	–0.09***	–0.03**	1				
11	1st Sem GPA	0.48***	–0.18***	0.01	0.10***	–0.14***	0.01	0.56***	0.39***	0.15***	–0.04***	1			
12	On-Campus	0.02*	–0.01	0.01	0.00	0.01	–0.00	–0.02	0.00	0.01	–0.03**	–0.01	1		
13	Total Courses Y1	0.39***	–0.08***	–0.06***	–0.02	–0.04**	–0.02	0.13***	0.09***	0.04***	–0.02	0.30***	0.04**	1	
14	Risk Total Y1	–0.05***	0.00	0.04***	–0.04**	0.04***	–0.01	–0.21***	–0.27***	–0.16***	0.05***	–0.25***	0.02	0.02	1

Note: Variable Definitions: **Fall-to-Fall Retention** (whether a student retained after 1 year, retained = 1, not retained = 0); **Gender** (male = 1, female = 0); **Age** (age at entry); **Race/Ethnicity** (White = 1, minority = 0); **First-Generation Status** (first-gen = 1, non-first-gen = 0); **Tuition Residency** (resident = 1, non-resident = 0); **HS GPA** (high school GPA); **ACT & SAT** (test score, ACT and SAT converted to ACT scale); **Student Classification** (freshman = 1, sophomore = 2, junior = 3, senior = 4); **Undeclared Major** (undeclared = 1, major declared = 0); **1st Sem GPA** (first-semester GPA); **On-Campus** (on-campus = 1, distance = 0); **Total Courses Y1** (total number of courses taken in their first year); **Risk Total Y1** (the number of high-risk courses taken in their first year).

Pearson's r was used in the correlation analysis because (a) variables are normally distributed, (b) relationship between the variables is linear, and (c) there are no outliers in the data.

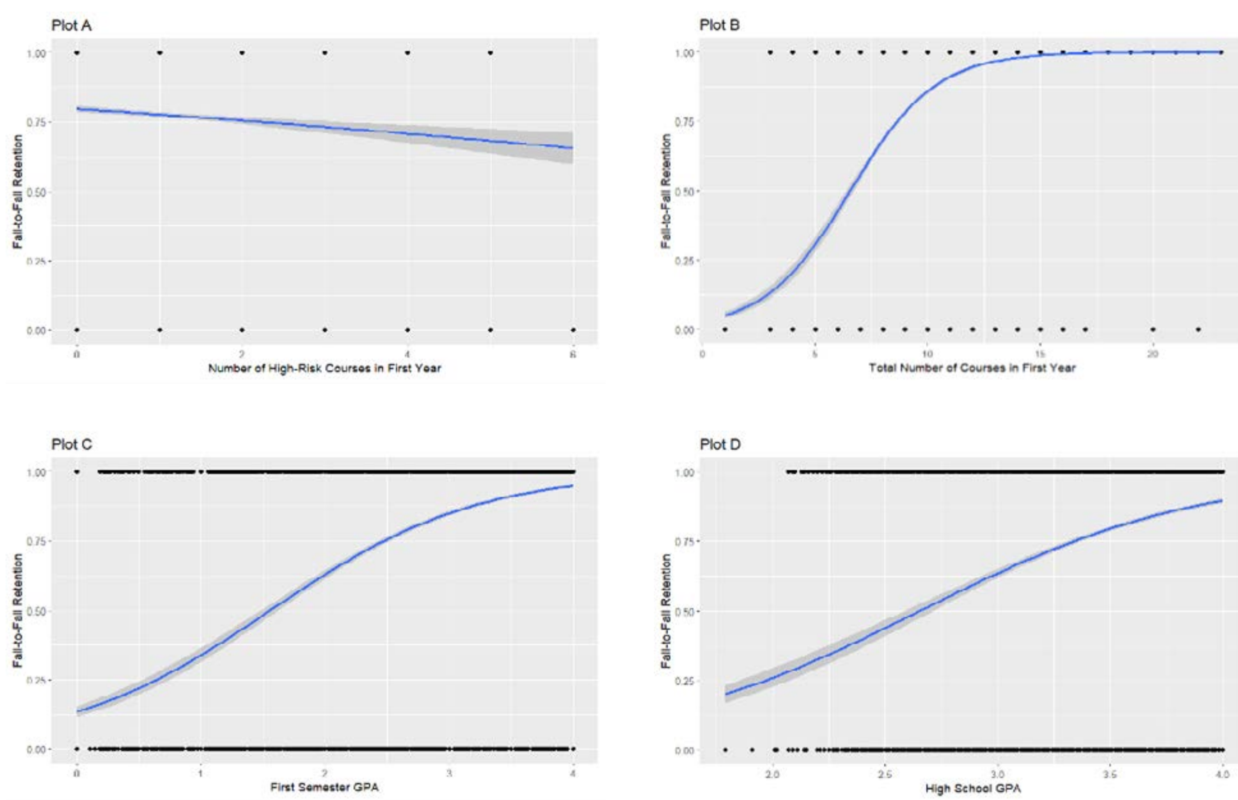
Correlation effect size: small $r = 0.10$, moderate $r = 0.30$, large $r = 0.50$ (Cohen, 1988).

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

The total number of high-risk courses taken in their first year (Risk Total Y1) had a negative correlation with Fall-to-Fall retention ($r = -0.05$, $p < .001$), but the effect size was very small according to Cohen (1988), which limits its practical significance. First-semester GPA had the strongest positive correlation with Fall-to-Fall retention, $r = 0.48$, $p < .001$, which is considered a moderate-to-large effect size (Cohen, 1988). This means that students who had relatively high first-semester GPAs were more likely to retain after 1 year. The total number of any courses taken in their first year ($r = 0.39$, $p < .001$) and high school GPA ($r = 0.30$, $p < .001$) also had moderate positive correlations with Fall-to-Fall retention.

The relationships between Fall-to-Fall retention and the total number of high-risk courses taken in the students' first year, the total number of any courses taken in their first year, first-semester GPA, and high school GPA were visualized using logistic regression curve plots (Figure 1). Figure 1 shows that students who take none to two high-risk courses tend to have a 75% or higher probability to retain; when students take more than three high-risk courses the probability of retaining decreases (Plot A). Students who take more than nine courses in their first year tend to have a 75% or higher probability of retaining; when students take ten or more courses the probability of retaining can be 87% or higher (Plot B). Students who have a first-semester GPA higher than 2.5 tend to have a 75% or higher probability to retain (Plot C). Students who have a high school GPA higher than 3.3 tend to have a 75% or higher probability to retain (Plot D).

Figure 1. Logistic Regression Curve Plots for Fall-to-Fall Retention



RQ3: HOW WELL DOES A COMBINATION OF STUDENT DEMOGRAPHICS, HIGH SCHOOL ACADEMIC BACKGROUND, UNIVERSITY ACADEMIC EXPERIENCE, AND FIRST-YEAR COURSE ENROLLMENTS PREDICT FALL-TO-FALL RETENTION?

Logistic regression was conducted to investigate the best model using the selected 13 predictor variables to predict whether a first-time, full-time student retained after 1 year (Fall-to-Fall retention).

The method of model selection is used to simplify the logistic regression model by removing variables (Dey et al., 2025; Starbuck, 2023). All 13 predictor variables were entered as independent variables in the base model/full model, and Fall-to-Fall retention was entered as the dependent variable. The base model was run with the binomial logistic regression analysis in R. Then the backward elimination method was used to simplify the model by removing the least significant variables iteratively based on *p*-value (MedCalc, 2024; Starbuck, 2023). Two methods for the model simplification were used, and the results were compared for cross-validation: (a) Only one variable with the largest *p*-value ($> = .05$) was deleted in each step, and the revised model was rerun until all variables were statistically significant ($p < .05$); (b) If $p > = .05$, the variable with the smallest log odds value (estimate) was deleted, and the revised model was rerun until all variables were statistically significant ($p < .05$). The results showed that the final models were the same after using both methods.

Table 7 presents the results of the logistic regression model predicting Fall-to-Fall retention of first-time, full-time students. When all seven predictor variables are considered together, they significantly predict whether a student is retained after 1 year. The coefficient values in Table 7 (i.e., log odds) indicate the unstandardized effect size of each predictor. It tells us the direction (i.e., positive or negative) and the strength of the relationship between the predictor and how likely that a student would retain. The results suggest that the odds of Fall-to-Fall retention are increasingly greater as first-semester GPA, high school GPA, tuition residency, and the number of total courses in their first year increase; the odds of retention decrease for first-generation students and students with an undeclared major. In addition, the first-semester GPA has the largest effect size, and the number of high-risk courses taken has the smallest effect size.

Table 7. Significant Predictors of First-Time, Full-Time Students' Fall-to-Fall Retention

Predictor	Coefficient	Std. Error	z value	Pr (>|z|)
(Intercept)	–6.60	0.33	–19.92	<0.001
First-Gen	–0.33	0.07	–4.47	<0.001
Tuition Residency	0.43	0.07	6.25	<0.001
HS GPA	0.43	0.09	4.91	<0.001
Undeclared Major	–0.23	0.12	–1.98	0.048
First-Semester GPA	0.99	0.04	23.63	<0.001
Total Courses Y1	0.40	0.02	21.15	<0.001
Risk Total Y1	0.07	0.03	2.13	0.033

It is noticeable that the number of high-risk courses in their first year (risk total Y1) had a positive logistic regression coefficient in the logistic model (coefficient = 0.07), but a negative correlation coefficient with Fall-to-Fall retention in the correlation matrix (r = –0.05). This might be because "the original relationship between the two variables is so close to zero that the difference in the signs simply reflects random variation around zero" (Falk & Miller, 1992, pp. 75–76).

Finally, the likelihood ratio for logistic regression was calculated in R to compare the likelihoods of two models: the null model (with only the intercept) and the final model (with seven predictors). The results showed that the difference in deviance between the two models was statistically significant (χ^2 = 2393.9, df = 7, p < .001), indicating that the final model provides a significantly better fit to the data than the null model. The model explained 39.9% (Nagelkerke R^2) of the variance in retention.

CONCLUSION

This research report examined the relationship between high-risk courses of Fall-to-Fall retention of the first-time, full-time students at a large public research university. The findings of this study reveal significant insights into the impact of high-risk courses on student retention rates. In this study, 21 courses are identified as high-risk courses, including Biology, Algebra, Trigonometry, Business Calculus, and Computer Science, among others. Hybrid and face-to-face courses are more likely to be high risk compared with online courses. STEM core courses such as Quantitative Reasoning, and Physical and Natural World are more likely to be high risk compared to non-STEM core courses like Communication and Human Culture. Math gateway courses are more likely to be high risk compared to English gateway courses.

Students in High-Risk Courses

The average number of high-risk courses taken in the first year was 1.08, with students who did not retain after 1 year taking more high-risk courses (1.17) than those who retained (1.05). This correlation between the number of high-risk courses and retention rates underscores the importance of managing academic risk to improve student outcomes. Pierre (2015) emphasizes the significance of academic risk-taking and its impact on adult learners, suggesting that strategic learning activities can support students who struggle with academic achievement.

Furthermore, the study highlights disparities among different demographic groups. American Indian or Alaska Native students had the highest average number of high-risk courses in their first year (1.38) and the lowest retention rate (52.4%) among all racial/ethnic groups. The age group of 25+ had the highest average number of high-risk courses (1.67) and the lowest retention rate (63.0%) compared to all other age groups. This suggests that older students may face additional challenges in managing academic risk, possibly due to balancing education with other responsibilities such as work and family.

Students who took three or more high-risk courses in their first year had the lowest Fall-to-Fall retention rate (72.2%), while those who did not take any high-risk courses had the highest retention rate (79.4%). This difference suggests that there is a critical need for institutions to carefully consider the academic load and support mechanisms for students enrolled in high-risk courses. For example, advisors can recommend students not taking more than three high-risk courses in their first semester or first year. Previous studies also support the importance of early predictors and early intervention for improving student success and retention rates (e.g., Baker et al., 2015; Daniel, 2022).

High-Risk Courses and Student Retention

The findings suggest that the number of high-risk courses taken in the first year is significantly negatively associated with student retention, meaning that students who enroll in fewer high-risk courses during their first year are more likely to retain after 1 year. When a student takes two or fewer high-risk courses, the probability of retention is predicted to be 75% or higher. This aligns with previous research by Haynes Stewart et al. (2011) and Salazar-Fernandez et al. (2021), which confirmed that course failure or high-failure rate courses negatively affect first-year university students' dropout or retention rates. This study further demonstrated that the negative correlation between high-risk courses and retention is statistically significant, even when considering other demographic information and previous academic performance. However, while the negative correlation between high-risk courses and retention is statistically significant, the effect size (r = –0.05) is very small, which limits its practical significance.

Among the other predictors of student demographics, high school academic background, and university academic experience, first-semester GPA, and high school GPA emerged as the strongest indicators of retention. Students with a higher first-semester GPA are more likely to retain after 1 year, with a GPA of 2.5 or higher predicting a retention probability of 75% or more. Similarly, students with a high school GPA of 3.3 or higher also have a retention probability of 75% or higher. These results are consistent with previous research that underscores the importance of academic performance in predicting student retention. For example, Estepp et al. (2019) found that high school GPA and first-semester GPA were highly correlated with freshman academic outcomes and retention. Their study demonstrated that first-semester GPA was moderately correlated with sophomore retention (r = .45), explaining 29.1% of the variance in retention. Additionally, the study by Hosch (2008) examined the predictive relationship between first-semester GPA and retention rate, suggesting "institutions trying to improve their one-year retention rates and subsequent graduation rates should continue to focus on student success in the first-semester" (p. 9). However, Hosch (2008) argues that graduation and retention rates alone are insufficient measures of educational effectiveness because these statistics do not account for differences in student effort or motivation to succeed. This perspective supports our findings, indicating that, while first-semester GPA is a strong predictor, other factors (e.g., course engagement, advising experiences) must also be considered to fully understand student retention. Furthermore, Westrick et al. (2015) conducted a meta-analysis examining the predictive validity of high school GPA, ACT scores, and socioeconomic status (SES) on college performance and retention. Their study found that high school GPA was a robust predictor of first-year academic performance and subsequent retention, reinforcing the importance of pre-college academic preparation. This meta-analysis supports our conclusion that high school GPA is a critical factor in predicting student retention.

In addition to GPA, other significant predictors identified in our study include tuition residency, total number of courses taken in the first year, first-generation status, undeclared major, and the number of high-risk courses taken in the first year. These factors contribute to a comprehensive understanding of student retention and highlight the need for targeted interventions to support students who are enrolled in high-risk courses.

Practical Implications

Based on the research findings, there are some practical recommendations for improving student success in the high-risk courses and their retention rate. High-risk courses present significant barriers to student success, but targeted interventions and instructional methods specifically designed for high-risk courses have been implemented in previous studies. For example, Norton et al. (2018) introduced a new instructional method called SCALE-UP (student-centered activities for large enrollment undergraduate programs) that "supports student collaboration and active learning by minimizing lecture time and focusing on hands-on problem solving in the classroom" (p. 42). They examined the impact of the method on the trend in DFW proportions for an introductory calculus course, and found the positive influence of SCALE-UP on reducing DFW proportions. Active learning techniques, which emphasize student engagement and participation, have also been effective in improving performance in high-risk courses (Higgs et al., 2021). Roberts et al. (2018) suggested that implementation of active-learning practices (e.g., in-class assignments, group work, problem solving, and discussion) into STEM courses demonstrated benefits, including better student learning and performance, and smaller achievement gaps among different student populations when compared to lecture-based approaches. In addition, collaborating with the tutoring center on the identified high-risk courses, especially in STEM majors, would ensure tutoring resources are available.

The findings of this study provide valuable insights into the impact of high-risk courses on student retention and the predictors of retention. While the negative correlation between high-risk courses and retention is statistically significant, the small effect size suggests that other factors also play a crucial role in student retention. Institutions should continue to explore comprehensive strategies that address the diverse needs of students and that provide targeted support to those enrolled in high-risk courses. First-semester GPA and high school GPA are the strongest indicators, but other factors such as tuition residency, course load, and first-generation status also play significant roles. Institutions should consider these predictors when developing strategies to improve retention rates and support student success. For example, consideration of student characteristics needs to be part of advising first-time students on whether they should take high-risk courses in their first year. Factors such as ethnicity, age, tuition residency, high school GPA, first-generation status, and undeclared majors should be balanced against the number and type of high-risk courses that students are advised to take in their first year. In addition, advisors and faculty members should offer support and resources for the undeclared students to determine which high-risk core courses they should take, and when they should take them.

Limitations and Recommendations

First, the results might not be generalizable because only one institution's data were used in this study. Certain subgroups, such as students aged 25 and older (n = 27) or racial/ethnic subgroups, are underrepresented, making it difficult to draw generalizable conclusions for these populations. Future research can use different data sources from additional institutions or different student populations (e.g., full time vs. part time, institution type, pre-COVID vs. post-COVID samples) to identify effective strategies for supporting diverse students in high-risk courses.

Second, the selection of variables is limited by the availability of a database for this study. The use of a single threshold (pass rate < 80%) to define high-risk courses may oversimplify the complexity of course performance. Additional factors, such as student engagement or instructor effectiveness, could provide a more holistic view. Future research should examine more variables related to high-risk courses for predicting retention using different data collection techniques such as student perspectives and experiences on high-risk course learning, advising, tutoring, and faculty/instructors, and so on.

Finally, the approach for model simplification or model selection has limitations, since it could exclude variables that might be important in combination with others. Future research should continue to refine the retention model, and should consider using other statistical methods (e.g., non-parametric tests, causal models) or qualitative methods to evaluate the correlations and investigate how the high-risk course experiences or performance differed by student backgrounds.

Significance

This study could be interesting for institutional research professionals and other higher education researchers, particularly those at large, public institutions. The topic is highly relevant to educators, administrators, and policymakers who are focused on improving student retention and success. The findings can contribute meaningfully to the growing body of research on student retention and offer practical recommendations for improving student outcomes.

Methodologically, the study uses a robust data set of 8,220 first-time, full-time students spanning five cohorts, allowing for meaningful longitudinal insights. The methods to identify high-risk courses and student characteristics, and the research process to develop a retention model using high-risk courses, can be helpful to similar institutions and could provide an example for reproducing similar studies at their own institutions.

Institutions frequently attribute students' underperformance to inadequate preparation. However, this study suggests there is an optimal number of high-risk courses that first-year students should enroll in for the highest chance of success. It also raises critical questions about the existence of high-risk courses and emphasizes the necessity for faculty, advisors, and administrators to prioritize the curriculums and delivery of these courses to improve student success.

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The authors declare that there is no conflict of interest.

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Did They Get What They Came For?

WORK-INTEGRATED LEARNING AND POSTGRADUATE EMPLOYMENT OUTCOMES

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About the Authors

Cassandra R. Kepple, PhD, Samantha Nix, PhD, Andrew Brady, and Jeckson de Andrade Silva are a team who have worked together in the Office of Institutional Research at Florida State University. The authors bring together decades of higher education practice and research experience, with emphases in student success and data analytics.

Abstract

In this study, we examined the relationship between work-integrated learning (WIL) participation and securing job offers. We used a sample of 18,966 graduation survey responses collected over 7 years at a large public research institution in Florida. Specifically, we investigated how this relationship may have changed post-COVID. In the 2016–2017, 2017–2018, and 2019–2020 surveys, we observed a negative relationship between WIL participation and securing a job offer; this relationship became positive in 2020–2021, however, and remained positive through the latest cohort, 2022–2023. We examined possible factors of this change, such as how students from different backgrounds engaged in WIL and how institutional policy affected them. These findings will be used by institutional research professionals to make suggestions for decisions regarding various programs at the institution as well as policies that are meant to support the post-graduation success of students. Beyond the emphasis of informing policy and practice on this specific campus, our intention for this study is to encourage further inquiry into the relationship between WIL experiences and postgraduate employment outcomes for students in other institutional contexts.

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INTRODUCTION

Students enter college with the expectation that their experiences and attainment of a degree will help them secure employment (Eagan et al, 2016; Pryor et al., 2007). As part of the college experience, many institutions provide opportunities outside the classroom that are meant to help students develop competencies to reach their career goals. Among other names found in existing literature, these activities are referred to as high-impact practices (Kuh, 2008) and work-integrated learning (WIL) (Cooper et al., 2010). While the terms for these activities vary, they consistently include experiential learning opportunities such as internships, cooperative education programs (co-ops), and practica (Cooper et al., 2010; Kuh, 2008). Each of these activities is meant to connect the knowledge and skills gained through coursework to real-world work settings. There is an overwhelming amount of evidence across the higher education literature pointing to a positive relationship between participating in activities such as WIL and other career preparation, and securing a job after graduation (e.g., Bist et al., 2020; Coker et al., 2017; Huber, 2010; Jackson & Bridgstock, 2021; Pascarella & Terenzini, 2005; Wyonch, 2020). Despite the wide array of positive findings from participation in these activities, some evidence shows this positive relationship can often be nonexistent, or the relationship can even be negative, for students with minoritized identities (Cocks & Thoresen, 2013; Moylan & Wood, 2016; Patton et al., 2015). Furthermore, institutions should continuously monitor the relationship between program engagement and student success outcomes to ensure quality and data-informed decision making (Fingerson & Troutman, 2019; Janice & Voight, 2016; Kinzie & Kuh, 2016; Mullin, 2012). In this study, our team engaged with this research to examine the relationship between WIL participation among seven graduating cohorts at a large research institution in Florida, spanning academic years before, during, and after the COVID pandemic.

Purpose

The purpose of this study was to longitudinally examine the relationship between participating in various work-related experiential learning opportunities and securing a job offer by the time of baccalaureate graduation. For brevity in this study, we use the term "work-integrated learning" (WIL) as an umbrella term for multiple experiential learning opportunities; see the Variables subsection in the Methods section for a list of these activities. Beyond examining the overall relationship between WIL participation and securing a job offer, we also looked explicitly into this relationship for minoritized students because of former research that suggests differential participation and outcomes for these populations (e.g., Finley & McNair, 2013; Kinzie & Gonyea, 2018; National Center for Educational Statistics [NCES], 2019; Wyonch, 2020). We examined the change in securing a job offer over time for students who are historically less represented in baccalaureate post-graduation employment outcomes: students from an underrepresented racial minority (URM), first-generation students, and Pell Grant–eligible students. Our data included graduating cohorts from 2016–2017 through 2022–2023. Because this range covers cohorts who graduated before, during, and after the heart of the COVID-19 pandemic—when there were significant shifts in educational practice and the labor market—we have used these three time-period categories throughout this paper. We recognize the challenges and innovations in offering WIL experiences during and after COVID, and we incorporate these concepts into our literature review and discussion of the results.

LITERATURE REVIEW

In the continuously evolving landscape of higher education, the integration of academic theory with practical, real-world application emerges as a guiding principle directing students toward success. WIL (Cooper et al., 2010), high-impact practices (Kuh, 2008), and other forms of experiential learning serve as dynamic educational strategies that adeptly interweave classroom-acquired knowledge with experiential work engagements. Due to the similarities, encompassing multiple activities such as internships and practica (Cooper et al., 2010), WIL and other experiential learning concepts allow students a comprehensive educational journey that extends beyond graduation. While there are many different terms referring to these activities, we first review literature related to WIL experiences and outcomes, and then, moving forward, we use "work-integrated learning" (WIL) to refer to all such activities throughout our paper.

Because students enroll in college expecting their experiences to help them attain their career goals, we examined extant literature on the connection between participating in WIL activities and postgraduate outcomes. Additionally, we explored existing evidence related to WIL participation and outcomes for traditionally underserved students.

Work-Integrated Learning in Higher Education

Employers and students alike recognize the importance for graduates to gain skills in college that will meet the needs of industry (DiBenedetto & Willis, 2020; Lisá et al., 2019; National Association of Colleges and Employers [NACE], 2022). Nevertheless, evidence from multiple studies shows that students often graduate without these necessary skills (Abbasi et al., 2018; Bist et al., 2020; Koc & Konz, 2009; Pittenger et al., 2006). Scholars have examined WIL and related experiences as an educational method that combines coursework with hands-on job experiences (Patrick et al., 2009; Prinsley & Baranyai, 2015); these experiences afford students the opportunity to use theoretical principles in practical situations (Billett, 2009; Ferns & Zegwaard, 2014; Orrell, 2004), and to develop those often-cited missing employability skills.

In this study, we use a conceptual framework of WIL. WIL is a comprehensive term for experiential learning activities that is used widely in an international context, with many higher education systems adopting the form of education broadly (Jackson & Wilton, 2016; Universities Australia et al., 2015; Wyonch, 2020). According to Cooper et al. (2010), WIL is "the process of bringing together formal learning and productive work" (p. xiii). WIL activities include, but are not limited to, practica, internships, fieldwork, co-ops, field education, service learning, and international service learning (Cooper et al., 2010). This explicit list of activities considered to be WIL aligns with other research on high-impact practices (Kuh, 2008) and experiential learning. Connectivity to the curriculum, the promotion of learning, and experiential elements for an experience are necessary to qualify as WIL (Cooper et al., 2010). Prominent WIL scholars emphasize that WIL activities, although they are inherently within the umbrella of experiential learning, nevertheless are ultimately a subset of experiential learning that specifically connects to industry and the workplace (Jackson & Dean, 2022; Patrick et al., 2009). While the term "WIL" has not yet been adopted by many researchers or practitioners in the United States, we determined that it is a term that fits well with the requirements of our study. We specifically examine student participation in experiential learning opportunities that directly relate to careers, and do not examine either a single type of activity such as internships or experiential learning in general.

Throughout three models of categorization, Cooper et al. (2010) conceptualize the meaning of WIL as a set of practices enabling students to actively participate throughout their college tenure, establishing direct connections between their academic learning and real-world workforce experiences. In addition to using the WIL framework, an abundance of research exists examining experiences akin to internships, co-ops, practica, and the like; that research often uses these terms interchangeably (e.g., Briel & Getzel, 2001; Main et al., 2020; Ryan et al., 1996; Wan et al., 2013). In this paper, we adopt the practice of using these terms interchangeably, mostly referencing them as “WIL” to align with the existing research on the multitude of experiential learning opportunities that can help enhance a student’s employability post-graduation.

Work-Integrated Learning Participation and Outcomes

Many studies provide evidence of a positive relationship between WIL and student success (e.g., Huber, 2010; Kuh, 2008; Pascarella & Terenzini, 2005; Waiwaiole et al., 2016), including postgraduate employment skills and outcomes (e.g., Bist et al., 2020; Jackson & Bridgstock, 2021; Simons et al., 2012; Wan et al., 2013). Smith et al. (2015) reported findings that were directly related to WIL participants being more work-ready, while Jackson (2017) found that participation in WIL helped students build a pre-professional identity.

The positive relationship between WIL participation and work-related outcomes is well documented across higher education literature, yet this positive relationship is not always consistent across populations. First, access to WIL activities remains inequitable. Data from the National Survey of Student Engagement (NSSE) and the NCES’s Baccalaureate and Beyond Longitudinal Study continue to show that students with characteristics such as being first-generation, having Pell eligibility, or belonging to a minoritized racial/ethnic group participate in internships at consistently lower rates compared to their majoritized peers (Kinzie & Gonyea, 2018; NCES, 2019). Individuals from marginalized groups may encounter discrimination and hurdles that hinder their engagement in these activities (Cocks & Thoresen, 2013; Moylan & Wood, 2016; Patton et al., 2015). Yet McCormick et al.’s (2017) study revealed that students belonging to marginalized groups who did participate in WIL activities expressed higher satisfaction levels with their college experience compared to their racial/ethnic counterparts who did not participate in WIL activities. Additionally, both Finley and McNair (2013) and Wyonch (2020) show that, when minoritized students participate in these activities, they often perceive their learning gains to be higher than the gains of their majoritized peers, and they secure wages similar to their majoritized peers as compared to those who did not participate.

The evidence of equity effects found by Finley and McNair (2013) and Wyonch (2020) provide an argument for the possible benefits of these activities, especially for traditionally underserved students. While it is important to recognize these possible benefits, it is also important to recognize the possibility of negative experiences directly related to their identities, as presented by evidence from Patton et al. (2015). Following suit, Kepple (2023) examined an overall relationship between WIL participation and employment outcomes, as well as explicit interactions among minoritized identities on this relationship.

Kepple (2023) found an overall negative relationship between WIL participation and securing a job offer, as well as a significant negative interaction for students who identified as URMs. In response to their findings, Kepple (2023) suggested that this unprecedented overall negative relationship might be due to improper implementation of WIL while the significant negative interaction for URMs may connect to findings of previous studies related to discrimination of minoritized populations during WIL activities and in the workplace (Cocks & Thoresen, 2013; Moylan & Wood, 2016; Patton et al., 2015).

Advocacy for WIL is grounded in the potential to provide students with valuable professional experience, to enhance their networks, and to signal their readiness for the workforce. Because of this potential, WIL activities have garnered significant attention across disciplines (Bolli et al., 2021). Positive impacts, ranging from increased wages to enhanced career self-confidence, underscore the multifaceted benefits of WIL (Bolli et al., 2021; Dailey, 2016; Ocampo et al., 2020). However, access to WIL experiences remains a hurdle for low-income, first-generation, and working students, limiting their opportunities for experiential learning and professional development (Finley & McNair, 2013; Kinzie & Gonyea, 2018; Main et al., 2020; McCormick et al., 2007). The diversity in WIL programs, varying in duration, location, and supervision, complicates research efforts to identify essential features for a high-quality experience.

In addition, studies by Bosco and Ferns (2014), Ferns (2012), and Smith (2012) provide evidence supporting the integration of WIL programs into university curricula. Recommendations for the effective implementation of WIL programs are also available, as highlighted by Freudenberg et al. (2011), Jackson (2015), O'Shea (2014), and Smith (2012). These recommendations include, but are not limited to, coordinating WIL activities with classroom instruction, developing precise placement design guidelines, encouraging cooperation between academics and practitioners, forging flexible and dynamic partnerships with outside organizations, and encouraging employer engagement.

While conventional WIL programs often involve physical placements, there is a growing trend toward incorporating simulated, virtual, authentic, and industry-based activities, as noted by Patrick et al. (2009) and Prinsley and Baranyai (2015). These supplementary activities present opportunities for creativity and exploration within the realm of higher education research and application.

Influence of COVID-19 on the Employment and Work-Integrated Learning Landscape

Prior to the COVID pandemic, the United States had a high employment rate. By the end of 2019, unemployment had dropped to a record low of 3.5% (Bureau of Labor Statistics [BLS], 2022a). Industries, including professional services, health care, and retail trade, were growing, and the labor market demonstrated steady employment growth. The pandemic, which started in March 2020 in the United States, resulted in historically high job losses. In April 2020 the national unemployment rate reached its highest level since the Great Depression, 14.7% (BLS, 2022a; Long & Van Dam, 2020). Then, in 2021 and 2022, the job market experienced a robust rebound. Employment in several sectors, including retail and professional services, had returned to or surpassed pre-pandemic levels by the end of 2021. By December 2021 the national unemployment rate had gradually decreased to 3.9% (BLS, 2022a). Bringing this issue to our regional context, from

2019 to 2020 Florida's unemployment rate increased from 3.3% to 7.7% (BLS, 2021). This shift in the labor market as a result of the pandemic led to changes by both employers and higher education institutions, especially related to the modality of services.

Technological advances and the disruptions caused by the COVID-19 pandemic in higher education have prompted institutions to explore virtual WIL experiences and other alternative approaches for collaboration with business partners (Klein & Scott, 2021; Patrick et al., 2009; Prinsley & Baranyai, 2015). While experiential learning programs have been impacted, this situation has also catalyzed a paradigm shift in learning, and prompted a reevaluation of conventional WIL methods. This paradigm shift presents an opportunity for in-depth exploration and understanding of the ramifications of various WIL models (Hora et al., 2021; Patrick et al., 2009; Prinsley & Baranyai, 2015). Notably, Hora et al. (2021) explored the landscape of online WIL experiences from 2020 to 2021. A few themes across their data were that (1) WIL participation was lower in 2020 to 2021 as compared to pre-COVID, (2) access and success barriers remained for traditionally underserved students, and (3) explicit attention was needed toward the infrastructure and implementation of WIL activities in this new modality. Youngblood (2020) qualitatively investigated the challenges with WIL becoming remote, and found that communication and understanding between WIL supervisors and students should be emphasized to make a successful online WIL experience.

While only a few studies exist on online WIL experiences during COVID-19, it is important to note that many remote opportunities persisted after in-person operations resumed. Prior to the pandemic, only 5% of internships were listed as remote. In 2021, 20% of internships were listed as remote (Konkel, 2021). Looking at the job market, only 2.5% of job postings were listed as remote or hybrid before the pandemic, with this percentage growing throughout the pandemic and peaking at around 10.4% in 2022 (Hiring Lab, 2025). Through 2023, the job postings for remote positions stayed higher than pre-pandemic, making up approximately 8% of all listings, while hybrid positions made up more than 31% of all listings (Culbertson, 2023). We are still learning about the nuances of shifting to remote WIL options and the effects of that shift on labor market outcomes, but it appears that remote and hybrid options are here to stay.

From this perspective, it is possible to say that WIL, especially internships, could stand as a cornerstone in enhancing student employability and success. Despite the positive change, challenges persist, and there are still disparities based on students' identities. Addressing these challenges, promoting inclusivity, and exploring innovative modalities are imperative as WIL practices continue to evolve. Ongoing research contributes to unraveling the intricate dynamics of WIL experiences, to providing an understanding of their impact on students, and to illuminating the broader landscape of higher education.

Research Questions

Our study was founded in our practical work related to examining WIL participation and postgraduate outcomes, our knowledge of existing higher education literature around this relationship, and our recognition that the world of higher education and WIL has forever been changed by the COVID-19 pandemic. To connect each of these concepts, we explored the relationship between WIL participation and post-graduation employment outcomes at the institution longitudinally, while also explicitly examining what this relationship looked like for minoritized students. Our study was guided by two research questions:

Research Question 1: How does the relationship between WIL participation and job offer change between 2016–2017 and 2022–2023?

Research Question 2: How do the rates of securing a job offer differ among minoritized students based on their WIL participation? Does this relationship change over time?

METHODS

In this study, we used quantitative data analysis to examine any relationship between participation in WIL activities and postgraduate employment outcomes. We used data from an exit survey collected from seven graduating cohorts of baccalaureate students and matched the results with institutional records related to demographics and academic progress. In this Methods section, we describe the study context, the sample, the variables, the analysis, and the limitations.

Study Context

This study was grounded in a single institutional context and developed from the work of an institutional research (IR) office that is committed to using data to engage with student success efforts. The institution is a large, public R1 university in Florida. Notably, this institution had implemented an experiential learning requirement as part of its graduation requirements starting with Summer 2019 matriculants. The requirement as stated in the undergraduate bulletin was to support experiences outside the classroom. In addition to traditional external WIL experiences, this requirement could be fulfilled through undergraduate research, international experience, service, and leadership opportunities. Students could receive credit for the requirement through successfully completing one of a specific set of courses, earning a certificate through the central career center, or substituting successful course completion in a different graduation requirement category (e.g., applying scholarly learning to an individual research or creative project) that had been implemented for several years prior to 2019. We interrogate the potential impacts of this new graduation requirement on the results of this study more in the Robustness Checks subsection of this paper.

To measure multiple outcomes, including the relationship between college experiences and job offers, the institution implements an exit survey. Approximately 3 weeks before their graduation date, the survey is sent to graduating bachelor's students asking about experiences at the institution and their plans after graduation. This survey has been in practice for more than a decade and is part of a collaborative effort between the offices of IR, Student Affairs, and the Career Center. Prior to implementation of this survey, the institution had periodically sent post-graduation surveys to alumni through ad hoc email campaigns and physical mailings.

The current survey is administered via a Qualtrics survey by the IR office. The survey is listed as one of the graduation requirements, and consequently the response rate is about 93% annually. The IR office consults several offices on a regular basis to keep the survey fresh and relevant.

Information that is collected in the survey is used for a variety of purposes, such as the following:

- To respond to surveys such as NACE, *US News & World Report*, and *The Princeton Review*
- To contribute to annual internal reporting to vice presidents and deans
- To contribute to program reviews and routine departmental reporting
- To contribute to ad hoc and other routine internal reporting
- To verify and update post-graduation contact information for alumni relations
- To offer an opportunity for graduates to connect with the Career Center as an aid for them to find employment

As part of the post-graduation outcomes process, IR also administers a 3-month follow-up survey to each graduate, whether they completed the survey or not. The 3-month follow-up survey focuses on the students' primary plan after college, and focuses particularly on those students who indicated pending employment or furthering education on the initial survey.

Additionally, IR conducts a knowledge rate search for those who indicated pending employment or furthering education on the initial survey and who did not complete the 3-month follow-up survey. This process includes a search of LinkedIn profiles for those who indicated employment as their primary plan and the National Student Clearinghouse collection for those who indicated furthering education.

Questions about experiences while attending the institution were asked only on the initial survey. These experiences included experiential learning opportunities that are designated and studied in this paper. For that reason, we focused on those students who had completed the initial survey, or who had completed both the survey and the 3-month follow-up, establishing the survey rate. For this paper, we matched the WIL information and the job placement information found in the survey rate of the post-graduation outcomes collection. (The survey questions are available in Appendix A.)

Sample

This study's population included seven cohorts of graduating seniors from a single institution. The sample was first limited by including only those who responded to the exit survey, making the sample approximately 93% of the graduates across 7 years. We then limited the sample to include only first-time-in-college (FTIC) students. Transfer students are excluded because they had less time to participate in these WIL experiences after matriculation to the institution. FTIC students are those who matriculated to the institution after receiving their high school diploma and who had not earned 12 or more college credits between their high school graduation and their initial enrollment at the institution. The final inclusion criteria for this study were for students to have stated their primary plan after graduation to be employment and for the students to have indicated they had already applied for a job. We focused on only those students who had applied for a job since applying is required to secure a job offer. Notably, across the entire sample, 91% of all graduates whose primary plan was employment had applied for a job. This percentage was consistent across the degree years, ranging between 89% (this low during the 2019–2020 graduation year) and 92% (this high during the 2018–2019, 2020–2021, and 2021–2022 graduation years). The range in the share of graduates whose primary plan was employment and who applied for a job was even more consistent when looking at the sample pre-, during, and post-

COVID: that range was 91% across each of those eras. Since there was no clear pattern of increasing application rate across the graduation years, we determined that we could control for this variable without biasing our results by limiting the sample to only those who had applied.

After each of these inclusion criteria was applied, we had a resulting analytical sample of 18,966 students. The primary source of information used in this study is historically collected survey data. Since every graduating student receives the survey, we recognize that we do not have a random sample. Instead, we have seven cohorts of student responses, averaging around a 93% response rate. This ultimately leads us to generally explore the population of the institution's graduates. We describe the sample in the Descriptive Statistics subsection of the section Findings.

All students in the sample graduated between Summer 2016 and Spring 2023. Cohorts were defined using the academic year such that Summer 2016, Fall 2016, and Spring 2017 graduates represented the 2016–2017 cohort, and so on. We further divided cohorts based on the timing of their graduation with the COVID-19 pandemic. Specifically, graduates in the 2016–2017, 2017–2018, and 2018–2019 years were labeled pre-COVID; graduates in the 2019–2020 and 2020–2021 years were labeled COVID; and graduates in the 2021–2022 and 2022–2023 years were labeled post-COVID. We used these COVID eras to examine our research questions.

Variables

The two main variables of interest in this study were participation in at least one WIL activity (independent variable) and securing a job offer (dependent variable). Both variables were derived from survey responses. In this study, we used the term "work-integrated learning" (WIL) as an encompassing term for various experiential learning opportunities available at this institution. The decision to equate these experiences was based on previous research (Cooper et al., 2010; Kepple, 2023) and consensus among a committee of WIL administrators at the institution. When we use the term "WIL" in this study, we are including the following experiences: internships, co-ops, fieldwork, student teaching, apprenticeships, and clinicals.

Additionally, the receipt of a job offer rather than the acceptance of a job offer was chosen as the dependent variable interest based on a previous study's use of the variable (Kepple, 2023). Kepple (2023) argued that receiving a job offer is an indicator of success in the search for employment while accepting a job offer is a form of success, but the decision to accept could be influenced by other factors. In the decision to use receipt of a job offer as the dependent variable, we are recognizing that the job offer in and of itself is a sign of success and is more inclusive than using acceptance of a job offer as the variable of interest.

In addition to our main variables of interest, we selected specific demographics and academic variables to include as controls in our models. We collected data on students' sex, race/ethnicity, first-generation status, Pell Grant eligibility, and final cumulative GPA, all obtained from the institution's official student records system. We also examined whether an interaction existed between WIL participation and race/ethnicity, first-generation status, or Pell Grant eligibility in predicting whether a student would receive a job offer. Since we observed possible interactions between minoritized identities and participation in WIL on predicting job offers, we dummy coded our variables with the minoritized characteristic as 1 and the majoritized characteristic as 0. This resulted in the following variables: URM (0 if race/ethnicity was White or Asian, 1 for all other race/ethnicity categories, excluding Race Unknown and Nonresident Alien), first generation (0 for continuing generation, 1 for first generation), and Pell eligible (0 for non-Pell, 1 for Pell). In addition to the noted minoritized identities and their possible interactions, we used sex as a control because it is a demographic characteristic we could easily collect; we also used students' final cumulative GPA as a proxy for their academic achievement.

Analysis

Given the high response rates of this survey, we chose to begin our discussion of the findings using results of a descriptive analysis since these statistics provide observational information related to our research questions. To check statistical significance between groups we also ran a series of inferential statistics. For the descriptive analysis, we first examined rates of securing a job offer and rates of participating in a WIL activity in each COVID era for the overall sample and then for each identity group (URM, first generation, and Pell eligible) separately (see Tables 2 and 3 in section Findings). We then analyzed the rates of securing a job offer given WIL experience across the three COVID eras (before, during, and after). For this analysis, we also first investigated the results for the overall sample before focusing on results for each identity group: by URM, first-generation, and Pell-eligible status. These results are visualized using line charts (see Figures 1 through 4 in section Findings).

Next, we sought to examine if differences in secured job offer rates were statistically significant based on WIL participation or student characteristic. For instance, we asked if there was a statistically significant difference in the job offer rate of URM graduates who participated in a WIL activity compared to the job offer rate of URM graduates who did not participate in any WIL activity. We utilized chi-square tests for these analyses. Finally, we extended our tests of statistical significance by predicting the probability of job offer, given the interaction between WIL participation and minoritized group membership, using logistic regression estimation methods. The advantage of this method is that it allows us to hold constant all our control variables and to account for error to better understand the potential weights of the WIL versus identity variables in the outcome of securing a job offer. Prior to running these logistic regressions, we generated pairwise correlations between all the variables in the model. Results were within the normal limit and did not suggest intercorrelative effects. For all inferential analyses, we determined statistical significance at the $p < .05$ level. We review the method used to answer each research question before presenting our findings.

Limitations

This study has several limitations we should acknowledge before sharing the findings of the analysis. First and foremost, this study is grounded in the context of a single institution. Derived from the work of an IR office at a large, public, R1 university in Florida, the results here may not be reflective of all institutions in the world or even all institutions in the United States; the results' transferability to other large, public, R1 institutional contexts may be limited dependent on state, student demographics, and graduation requirements.

Second, as with most research arising from IR offices, the post-graduation employment outcomes here were derived from self-reported data. Although it is common to benchmark and even make policy decisions from this type of post-graduation employment outcome data, we acknowledge that self-reported information is subject to possible inaccuracies. Graduates may not know for sure their employment status at the time of the exit survey (i.e., at the time of graduation for this study) or they might lie, inflate, or deflate their employment status. Previous research provides evidence that self-reported student data can produce biased results, and that using a methodology such as state employment and salary may provide data that are more reliable (Bryant, 2021). Many IR offices do not have access to these forms of data sources, however. Additionally, the self-reported nature of these data means we do not have clear, consistent data on the compensation graduates received from their WIL experiences. Due to this limitation, this study cannot speak to any relationships between paid/unpaid WIL activities and employment outcomes.

FINDINGS

Descriptive Statistics

Before examining the relationship between WIL participation and securing a job offer, we first built a descriptive profile of the population. We focused this profile on the student characteristics that we used as controls in our regression model and examined for differential outcomes (Table 1). Of the 18,966 survey respondents who met our inclusion criteria, 25.7% qualified as first generation, 21.5% were Pell eligible, 33.1% were categorized as an URM, and 40.4% identified as male. The average GPA was 3.3. There were more than 4,000 graduates in each identity group of interest, thus reducing concerns in the inferential analyses of performing statistical tests on small sample sizes. Furthermore, the meaningful proportion of minoritized graduates in the overall population supported our efforts to examine outcomes for these groups.

Table 1. Sample Characteristics

	Sample (*n* = 18,966)	Job Offers	WIL Participants
Identity Group			
First generation	25.7%	24.6%	24.2%
Pell eligible	21.5%	20.6%	20.9%
URM	33.1%	31.7%	32.0%
Male	40.4%	40.3%	37.7%
Final GPA			
Average	3.32	3.36	3.38
Median	3.37	3.38	3.42

Note. The sample includes students who were FTIC, whose primary plan after graduation was employment, and who had indicated that they had applied for a job.

We next examined the composition of graduates who had both received a job offer and participated in WIL to compare the representation of minoritized populations in these variables to their representation in the full sample. Among those who received a job offer, 24.6% were first-generation students, 20.6% were Pell-eligible students, and 31.7% were URM students. Among WIL participants, 24.2% were first generation, 20.9% were Pell eligible, and 32.0% were URM. While the share of each minoritized group within job offer recipients and WIL participants were all fairly similar to their representation in the whole sample, traditionally underserved populations secured job offers and participated in WIL activities at lower rates than their majoritized peers. Moving forward from this descriptive profile, we explored securing job offers and WIL participation across each COVID era and dissected these findings by student characteristics.

JOB OFFERS BY COVID ERA

Because we have framed our study around the differences that could be occurring due to the COVID-19 pandemic, it is pertinent for us to focus our analyses on these time periods rather than looking at the seven cohorts as a singular group. We first looked at overall job offer securement by COVID era, and found that overall job offers decreased by 3.7 percentage points from pre-COVID to COVID, but then rebounded and even increased slightly post-COVID (Table 2). When examining each of the minoritized identities in our analysis, we saw similar results for each identity as compared to the overall (Table 2). Notably, URM students had the largest decrease between pre-COVID and COVID (–5.7 percentage points) and subsequent greatest increase between COVID and post-COVID (+7.7 percentage points). On the other hand, the pattern for first-generation students had the smallest changes across the three eras.

Table 2. Secured Job Offers by COVID Era and Identity

	Pre-COVID	COVID	Post-COVID
Job Offers	73.9%	70.2%	75.7%
First generation	70.5%	68.1%	72.5%
Pell eligible	70.3%	67.3%	73.0%
URM	71.4%	65.7%	73.4%

WIL PARTICIPATION BY COVID ERA

When we examined WIL participation across COVID eras, we found a completely different pattern than we did with job offers. Unlike job offers, overall participation rates for WIL activities increased across COVID eras, with a dramatic increase between COVID and post-COVID eras (+8.2 percentage points) (Table 3). We generally found this same pattern across different identities (Table 3). We also found that URM students had the greatest increase in WIL participation across time, going from 52.7% pre-COVID to 70.0% post-COVID. This 17.3-percentage-point change was not only the largest increase over time, but also, among the three identity groups examined, URM students went from the lowest pre-COVID participation to the second-highest post-COVID participation, switching places with first-generation students.

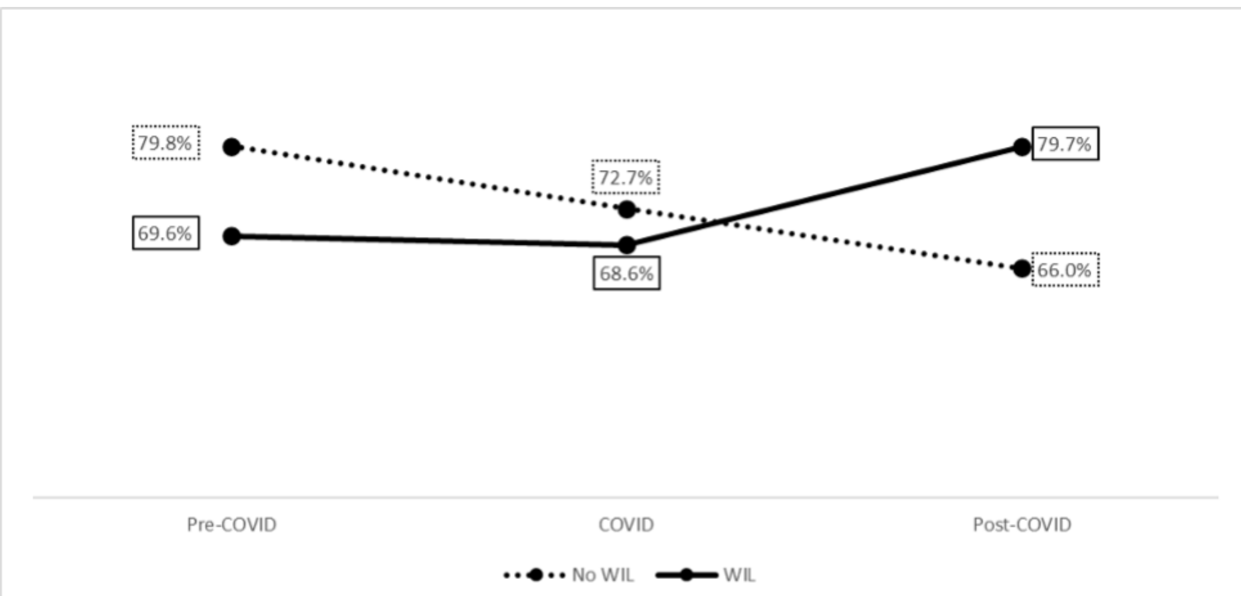
Table 3. Work-Integrated Learning Participation by COVID Era and Identity

	Pre-COVID	COVID	Post-COVID
WIL participation	57.6%	62.8%	71.0%
First generation	54.4%	58.3%	67.6%
Pell eligible	54.6%	60.7%	70.3%
URM	52.7%	61.9%	70.0%

Research Question 1: How Does the Relationship between Work-Integrated Learning Participation and Job Offer Change between 2016–2017 and 2022–2023?

After examining job offers and WIL participation separately, we compared the rates of securing a job offer by WIL participation across COVID eras to address the first research question. We found that, in the pre-COVID era, students who did not participate in WIL activities secured job offers at a higher rate than those who did participate in WIL. As expected, job offer rates for both groups decreased during COVID. Then, post-COVID, we saw a reversal in the pre-COVID finding: students who participated in WIL secured job offers at higher rates than students who did not participate in WIL (Figure 1).

Figure 1. Secured Job Offers by Work-Integrated Learning Participation and COVID Era



The striking differences in the rates of securing a job offer based on WIL participation over time, along with the reversal in the relationship between these two variables, justified an examination of the relationship with inferential statistics. To answer Research Question 1, we first tested if the differences in job offer rate for WIL participants versus nonparticipants shown in Figure 1 were statistically significant using chi-squared tests. The tests confirmed that the gap between WIL participants and nonparticipants in job offer rates were statistically significantly different for each COVID era. The chi-squared tests measure only if the descriptive statistics we observed were statistically different, not the magnitude of the difference, however.

We then tested if these statistical differences would hold up after controlling for observed variables. We built a logistic regression model predicting securing a job offer by participation in WIL activities and controlling for first-generation status, Pell eligibility, URM status, sex, and final cumulative GPA. To handle the element of time, we developed multiple models. First, we included a categorical variable for COVID era in the model along with the stated controls. These results showed that, holding all else constant, the odds of securing a job offer in the post-COVID era were positive compared to the pre-COVID era, although the effect size is relatively small (odds ratio [OR] = 1.08; $p = .05$) (Appendix B, Table B1). We then interacted the categorical variable for each COVID era with WIL participation, and found a meaningfully statistically significant difference in the probability to receive a job offer post-COVID compared to a job offer pre-COVID. Specifically, the odds of securing a job offer for post-COVID WIL participants were about 3.5 times higher than the odds for pre-COVID WIL participants (OR = 3.54; $p < .00$) (Appendix B, Table B2).

We then analyzed differences over time by limiting the observations in each model based on the COVID era. Therefore, we ran the logistic regression model three times: once with respondents who graduated in 2016–2017 through 2018–2019 (the pre-COVID era), once with respondents who graduated in 2019–2020 and 2020–2021 (the COVID era), and once with respondents who graduated in 2021–2022 through 2022–2023 (the post-COVID era). The results broadly followed the pattern shown descriptively. The pre-COVID and COVID models each showed a significant negative relationship between WIL participation and securing a job offer (pre-COVID: OR = .541, $p < .00$, COVID: OR = .800, $p < .01$), net of all other effects. Again, following the descriptive results, the post-COVID model showed a significant positive relationship between participating in WIL and securing a job offer (OR = 2.05, $p < .00$), holding all else constant. Therefore, the negative association between WIL participation and securing a job offer seen in the pre-COVID and COVID eras and the positive association between the same variables post-COVID was statistically significant even after controlling for observed variables. The results of each regression model are shown in Appendix B, Table B3.

Research Question 2: How Do the Rates of Securing a Job Offer Differ Among Minoritized Students Based on Their Work-Intgrated Learning Participation? Does This Relationship Change Over Time?

To further investigate the reversal in the relationship between WIL participation and securing a job offer pre- versus post-COVID, we examined this pattern descriptively for each characteristic of interest. We visualized our findings in line charts (Figures 2–4).

Regardless of the identity group evaluated, we found that the relationship between participating in WIL and securing a job offer seemed to flip from negative to positive between the pre- and post-COVID eras. In addition, in each analysis we found that minoritized WIL participants (solid lines with circles) went from having the lowest job offer rates pre-COVID and during COVID to having the second-highest job offer rates, second only to WIL participants with majority identities (solid lines with squares). Descriptively, first-generation, Pell-eligible, and URM students who participated in WIL had lower job offer rates than their peers pre-COVID and during COVID, but received some benefit from those experiences post-COVID.

Figure 2. Secured Job Offers by Work-Integrated Learning Participation and First-Generation Status across COVID Eras

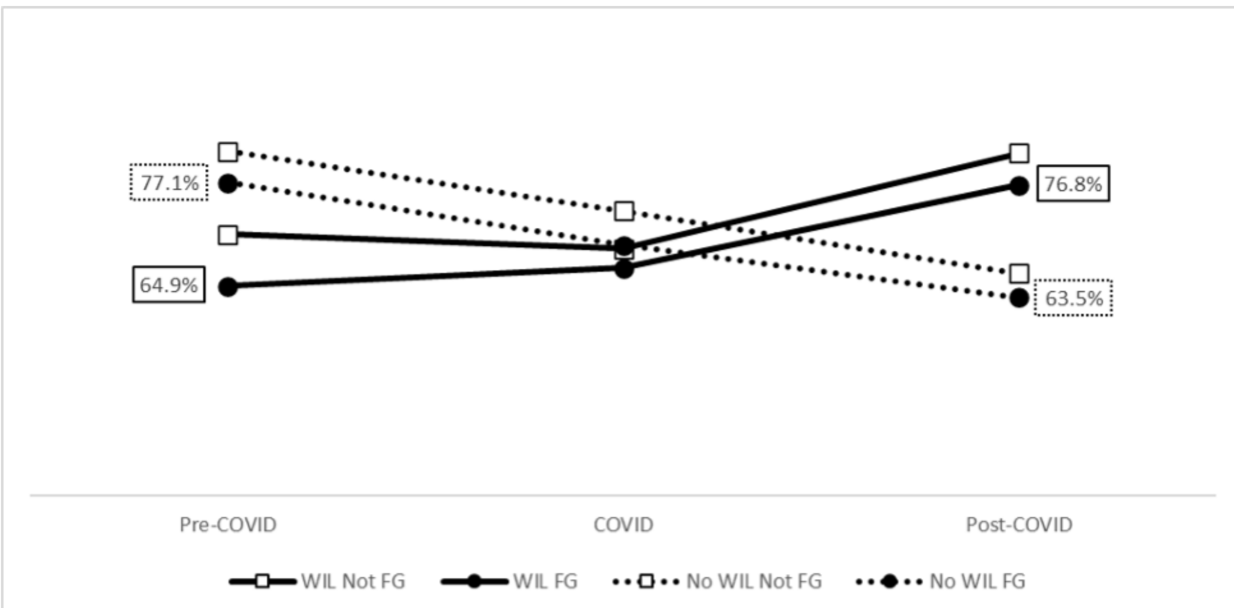


Figure 3. Secured Job Offers by Work-Integrated Learning Participation and Pell Eligibility across COVID Eras

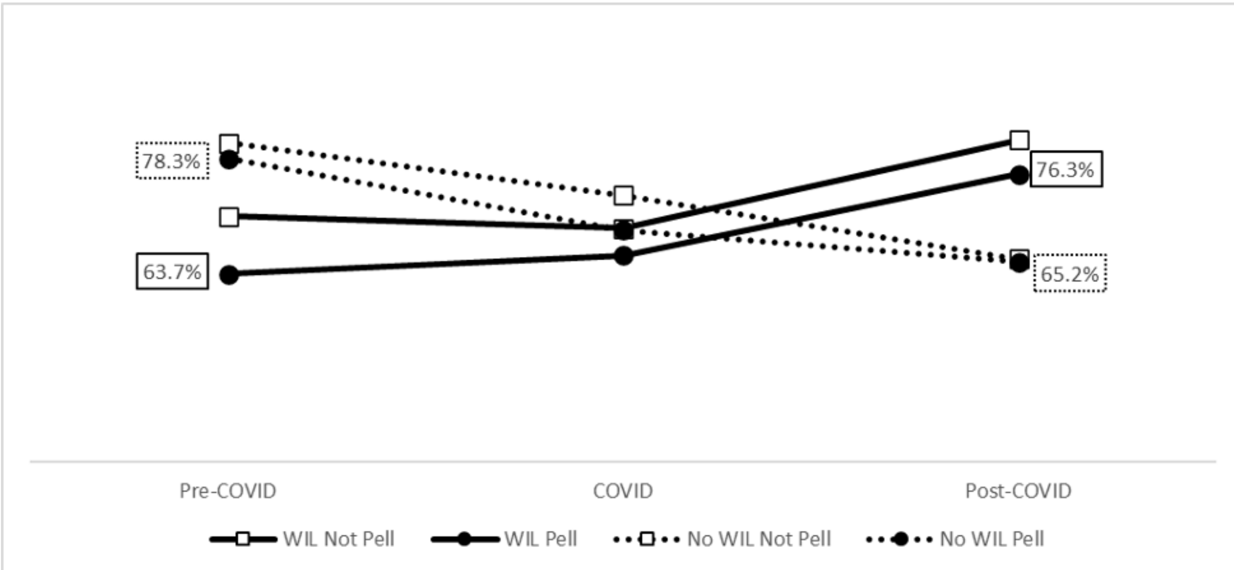
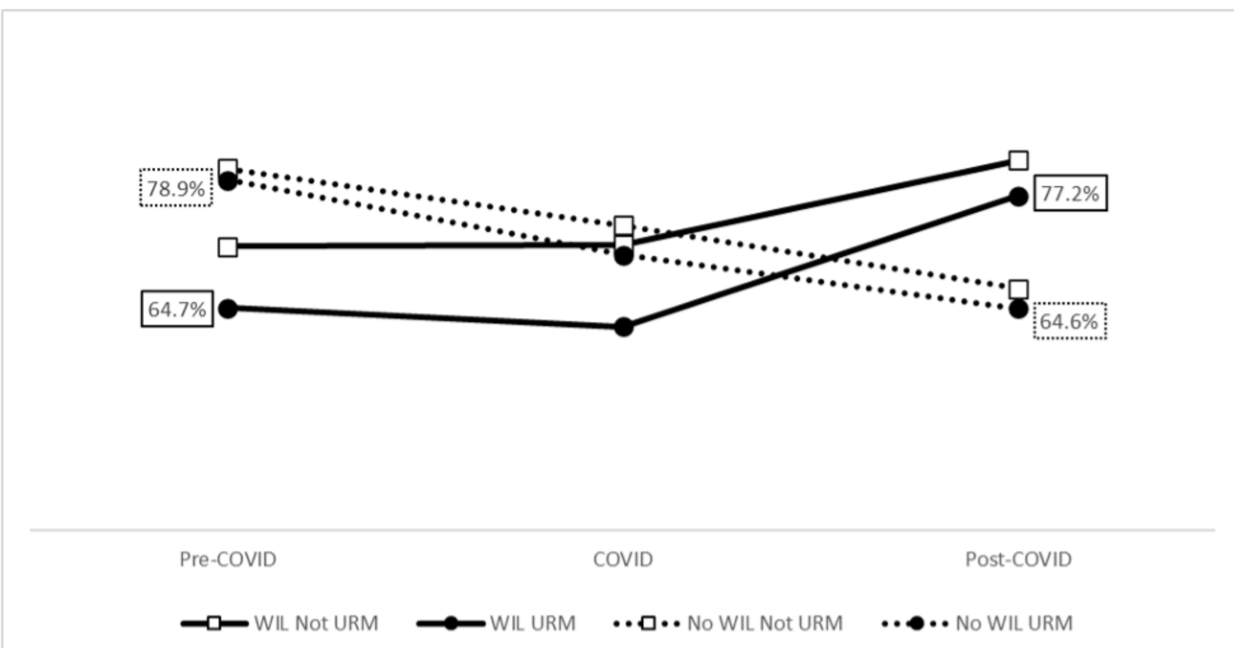


Figure 4. Secured Job Offers by Work-Integrated Learning Participation and Underrepresented Minority Status across COVID Eras



We tested the differences in job offer rates across time (a) between WIL/not WIL participants within minoritized student characteristic group (comparing solid lines and dotted lines with the circles) and (b) between minoritized/majoritized groups within WIL participants (comparing solid lines with circles or squares), both using chi-squared tests. Across all the comparisons for the (a) analysis, we found statistically significant differences for the pre-COVID and post-COVID eras, meaning WIL was statistically negatively related to securing a job offer pre-COVID, but statistically positively related to securing a job offer post-COVID for first-generation, Pell-eligible, and URM students. However, during the COVID pandemic the negative relationship was statistically significant only for URM students. For Pell-eligible and first-generation students, there was no statistically significant difference in job securement rates based on WIL experiences during COVID. Similarly for the comparisons in the (b) analysis, we found statistically significant differences between minoritized and majoritized WIL participants in secured job offer rates pre- and post-COVID. During COVID there was only a statistically significant difference in the secured job offer rates of WIL participants by URM status.

The way that these findings for URM students differ compared to results for first-generation and Pell-eligible students is worth further synthesis. In Figure 4, we see that URM students had the largest decline in securing a job offer during COVID, and, more specifically, we see URM students who participated in WIL dropped further in their job offer rates than the URM students who did not participate in WIL during the pandemic. In fact, this was the one case when the difference in job offer rates for the minoritized versus majoritized WIL participants during COVID was found to be statistically significant.

As shown in the overall analysis and across the other groups, URM WIL participants' job offer rates rebounded in the post-COVID era. What stands out, however, is that the rebound in job offer rates for URM WIL participants between the COVID and post-COVID eras was a statistically significant and practically meaningful 15-percentage-point change. Although URM WIL participants had statistically lower rates of securing a job offer during the pandemic, they were much more likely to find employment post-COVID.

Holding all else constant using logistic regression estimation methods, the differences in job offer rates between minoritized graduates and their majoritized counterparts was still statistically significantly different (ORs ranged .85 – .92, p-values ranged .000 – .047) (Appendix B, Table B1). However, given the descriptive findings, we knew that this relationship likely varied based on WIL participation and COVID era. Models with interactions between COVID era and identity, and interactions between COVID eras, identity, and WIL participation, yielded null results. In other words, once we had controlled for everything else in the model, there is no evidence that the predicted job-offer rates differ for specific student characteristics groups given their WIL experiences in conjunction with time. To analyze possible changes in outcomes for students who hold multiple underrepresented student characteristics, we ran two-way interactions with combinations of each of the identities together, as well as a three-way interaction across each COVID era. We found no statistically significant evidence for any possible identity interactions in that analysis.

Integrating interactions between student characteristics and WIL also yielded null results, with the exception of the interaction between URM and WIL (OR = .86; p = .037). Additionally, integrating a four-way interaction between WIL, first-generation, Pell-eligible, and URM participants returned a significant negative result only within the post-COVID era, although the effect size is relatively small (OR = .42, $p < .05$). Notably, when looking at this four-way interaction within each COVID era, we found the interaction to be statistically significant only within the post-COVID era. Upon further investigation, we found that the student profile that had the largest difference in predicted probability of securing a job offer based on WIL participation was the profile of students who identified as first generation, Pell eligible, and non-URM. Students with this combination of identities who participated in a WIL had a predicted probability to secure a job offer of 82.9% as opposed to 59.7% for students in the same identity categories who did not participate in WIL. When examining students who held all three underrepresented characteristics (first generation, Pell eligible, and URM), we found that those who participated in WIL had a 71.9% predicted probability to secure a job offer as opposed to 65.7% for those who did not participate in WIL. While we did find a significant interaction in this case, only 568 students, or 9.9%, in the post-COVID portion of the sample, exhibited this profile. Because this represents such a small amount of the study sample, and the study was designed to explore identities but not intersectionality, we do not feel we have enough information to pull inferences from it. We do want to acknowledge the findings, however. It is possible that this method of using interactions between multiple categorical variables could obscure differences that seem obvious in descriptive statistics. Furthermore, the significant interaction between WIL and URM was less interpretable when not considering time.

Therefore, we utilized our method of estimating logistic regression models of securing job offer given WIL participation, student characteristics, and final cumulative GPA separately for each COVID era. In this analysis, we found that each minoritized identity was significantly negatively related to securing a job offer pre-COVID (OR ranges .86 – .87; *p*-value ranges .015 – .042) with only URM identity maintaining this significantly negative relationship in the COVID and post-COVID eras (OR ranges .76 – .87; *p*-values range .000 – .049) (Appendix B, Table B3). Adding interactions between WIL participation and identity for each COVID era, we found no significant interactions (Appendix B, Tables B4–B6). The lack of any significant interaction between WIL and identities in each COVID era suggested that the overall changes in the relationship between securing a job offer and WIL are mostly being driven by changes with WIL participation rather than with students' identities.

These analyses showed that the gap in securing a job offer between WIL participants and nonparticipants with minoritized identities decreases from pre-COVID to post-COVID. Additionally, WIL participants began to have higher success rates in securing a job offer post-COVID as compared to peers with similar identities who did not participate in WIL. Participating in WIL was positively related to higher securement of job offers post-COVID for the overall sample as well as for minoritized students.

Robustness Checks

As part of our analysis and the review process, we explored two key questions about the inclusion of variables: about (1) degree field of study and (2) the potential impact of the experiential learning graduation outcome at this institution. We developed additional models to evaluate the inclusion of these variables, and we report on the results here.

Higher education research has included much discourse on the importance of field of study on student experience and post-graduation outcomes. Since the nature of career development can vary widely based on student major, it is reasonable to assume that field of study can be associated with variation in post-graduation outcomes. To test these associations, we developed a seven-category field of study variable: business, education, fine arts, health, humanities, sciences, and social sciences. These categories were first developed using the 2020 Florida Board of Governors (BOG) Program of Strategic Emphasis (PSE) list to designate classification of instructional programs (CIP) codes that fell into the following categories: education, health, and STEM (science, technology, engineering, and mathematics). This initial list was chosen due to institutional context: this institution is in Florida. Acknowledging research showing differential outcomes for physical and life sciences versus social sciences, we then took the BOG PSE STEM category and disaggregated it into sciences versus social sciences. The BOG PSE list was developed to support industry in Florida specifically, so some CIP codes either were not categorized into one of their categories or were given a category not meaningful to non-Florida contexts, such as Gap Analysis or Global. We reviewed CIP categories and developed the additional business, fine arts, and humanities categories, moving CIP codes into them as apparent to the IR office. The final crosswalk of CIP codes to field of study has been published by the IR office for more than 3 years and has been used extensively for both data requests and data use by researchers external to the office, providing some reliability checks. We included this field of study categorical variable into the models discussed in the Findings section.

There were very few changes in the main results, suggesting that the inclusion of field of study to our models does *not* provide additional context or meaningful insights. Specifically, for Research Question 1 investigating job offers by WIL participation and COVID era, there were no changes in the direction and statistical significance of variables reported in the findings. Students who participated in a WIL experience were more likely to secure a job post-COVID compared to pre-COVID, regardless of whether or not we control for field of study. For Research Question 2, investigating the interaction between WIL and identity, adding the field of study continued to yield no additional insights. There were no differences in the direction or statistical significance with the inclusion of field of study. Regardless of field of study, students of all identities seemed to have higher rates of securing job offers post-COVID, especially if they participated in WIL. For both research questions, inclusion of field of study yielded differences within a tenth of a point. Since this study was not explicitly concerned with investigating differences in student experience based on major or industry and to use the most parsimonious models available, we do not include field of study in our final models.

We additionally recognize that the institution studied in this project had implemented a new experiential learning graduation requirement as described in the Study Context subsection. This study is concerned with FTIC graduates from seven graduating cohorts from 2016–2017 to 2022–2023. The students matriculating under the new experiential learning requirement (starting in Summer 2019) were expected to graduate in Spring 2023, within the last graduation cohort included in this study. Those students make up about 15% of the total population in this study. It is possible that the implementation of the experiential learning graduation requirement supported the findings in this study. Although a single graduation cohort out of seven would not be expected to drive the results, the development of the experiential learning requirement may have resulted in increased infrastructure for the identification of WIL opportunities and support of learning outcomes.

We therefore examined the occurrence of successful experiential learning course completion across the graduation cohorts. We found equitable rates of earned credit, between 20% and 30%, across most cohorts, with the Spring 2023 graduates at the lowest rate at 18%. There are several potential reasons we have observed similar experiential learning course completion rates across the graduation cohorts, with the last cohort having the lowest rates. First, students who had the graduation requirement in the last graduation cohort would have had the least amount of time to take these courses, since this would be exactly 4 years to graduate. Second, the graduation requirement could be fulfilled through multiple avenues: course completion for that specific graduation requirement, course completion for a different graduation requirement that had already been implemented for several years, or a certificate from the central career center. Since only the last cohort in our study had this requirement, which comprises 15% of the overall population, students in this transitionary period behaved in the same way as prior cohorts by taking more courses in the other graduation requirement. This study does not capture the impact of the experiential learning graduation requirement policy change because there are not enough students who would have been impacted to fairly evaluate it. The evaluation of that graduation requirement is beyond the scope of this paper.

DISCUSSION

In this study, we analyzed the relationship between students participating in WIL and securing job offers by the time of graduation across seven cohorts, with an emphasis on the influence the COVID pandemic had on this relationship. Additionally, based on previous literature that shows access and success barriers for minoritized students (Cocks & Thoresen, 2013; Moylan & Wood, 2016; Patton et al., 2015), yet possible equity effects for them if they participated in WIL (Finley & McNair, 2013; Wyonch, 2020), we examined this relationship specifically for first-generation, Pell-eligible, and URM students. Generally, we found that rates of securing a job offer took a hit during the COVID-19 pandemic for graduates at this institution. The rates of securing a job offer returned to pre-pandemic levels in the post-COVID era.

Interestingly, where there had been a negative relationship between WIL participation and securing a job offer in both the pre-COVID and COVID eras, in the post-COVID era there was a positive relationship. This shift in the relationship from negative to positive was found both descriptively and inferentially, after holding demographic variables and final GPA constant. The reversal of the relationship between WIL participation and securing a job offer from negative to positive was consistent across minoritized populations descriptively. However, looking at the interactions between WIL and minoritized identities, the differences were not significant inferentially. This shows that there is no evidence that outcomes for WIL participants differ based on students' identity. Additionally, the overall regression with no interactions and with WIL as the standalone independent variable was quite significant and showed a reversal in the direction of the relationship post-COVID. These findings suggest that the WIL activity alone supports securing a job offer in the post-COVID era.

When exploring the outcomes, we found in the pre-COVID and COVID eras that minoritized students who participated in WIL had the lowest likelihood of securing a job offer, whereas post-COVID these students saw some benefit to their WIL experiences. Descriptively, in the post-COVID era, minoritized students who participated in WIL had higher secured job offer rates than their non-WIL counterparts. In fact, minoritized students who participated in WIL had secured employment rates that were second only to their majoritized counterparts who also participated in WIL. Furthermore, the gaps between minoritized and majoritized WIL participants in their secured job offer rate closed in the post-COVID era compared to the pre-COVID era.

Possible Explanations

Based on our findings and extant literature, we posit two possible explanations for the results of this study: increased remote opportunities/quality of experiences, and increased value for WIL experiences. We explore these possible explanations below.

EXPLANATION 1: INCREASED REMOTE OPPORTUNITIES/QUALITY OF EXPERIENCES

Our analysis showed that more students participated in WIL in the post-COVID era than in the pre-COVID and COVID eras. There was a 13.4-percentage-point increase in WIL participation for the entire sample, with a 13.2-percentage-point increase for first-generation students, 15.7-percentage-point increase for Pell-eligible students, and 17.3-percentage-point increase for URM students. The institution implemented policy changes in 2019 requiring newly matriculating students to participate in WIL-like experiences as part of graduation requirements. The cohorts of students who received that mandate have not fully flowed through to the graduating cohorts in this study, but the availability of the courses and programs related to that policy change could have benefited the students in this study, nonetheless. It is also likely that the move of jobs to remote work opened opportunities for more college students to participate in WIL remotely. This institution is in a small- to medium-sized city, with the closest metropolitan area approximately 3 hours away. Not only did the number of remote WIL listings quadruple during the pandemic (Konkel, 2021), but also the number of job postings offering remote or hybrid options increased, and even stayed afterward, with 38% of listings citing work locations alternative to in-person-only options in 2023 (Culbertson, 2023). Whereas pre-COVID cohorts could have struggled to identify in-person opportunities in the relatively low-population area of their university, post-COVID graduates benefited from remote work options.

Furthermore, minoritized students may not have experienced the level of discrimination in remote WIL that had been found in prior research on traditional, in-person WIL experiences. Prior research shows that minoritized students and employees sometimes report discrimination in workplace environments based on their identities (Cocks & Thoresen, 2013; Moylan & Wood, 2016; Patton et al., 2015). While the research related to online experiences during COVID is limited, Gutzwa (2022) noted in their study on Trans* student experiences in the classroom that the students in their study reported feeling more comfortable and experiencing less discrimination in an online class than in person. We would like to explore this concept further as it applies to WIL experiences, since it supports our findings, but recognize this would best be examined qualitatively in a future study.

EXPLANATION 2: INCREASED VALUE FOR WORK-INTEGRATED LEARNING EXPERIENCES

All students who participated in a WIL experience enjoyed greater rates of receiving job offers in the post-COVID era compared to WIL participants in the pre-COVID era. This signals that, post-COVID, either participants gained more job skills from WIL experiences, or those with WIL experiences became more valuable to employers, or a mix of both. The post-COVID era also included the Great Resignation, when remote and alternative work opportunities opened up more job opportunities for seasoned employees, and therefore more entry-level positions for new workers (BLS, 2022b). Employers seeking to fill vacant positions could also have found WIL experiences more valuable during this period as a form of work experience. It is consistently cited in the literature that employers are looking for the kinds of skills in graduates that should be attained with WIL participation (DiBenedetto & Willis, 2020; Gray, 2024; Lisá et al., 2019; NACE, 2022). It is possible that employers began to look more toward opportunities such as WIL as part of their holistic resumé review in response to an increased need for additional skilled workers because of the Great Resignation as well as the fact that students were not able to participate in many other activities such as student organizations or community service at the same level as they did pre-pandemic.

Conclusion

We examined the relationship between participating in WIL and securing a job offer by the time of graduation for seven cohorts of graduating students at a large public research institution in the southeastern United States, and found unexpected, yet positive, results. Recognizing the massive changes the world went through during the COVID-19 pandemic, we put a COVID-era lens across the cohorts of students. When examining pre-, during, and post-COVID eras, we found major changes to the relationship between WIL participation and securing a job offer, namely going from a significant negative to a significant positive relationship. Based on evidence in the literature as well as practical knowledge, we broke down this relationship to examine whether there were differences for students with select minoritized identities—first-generation, Pell-eligible, or URM status. While we found no significant interaction for these identities, we do see that the positive change in the overall WIL relationship persists for students with these identities, with students in the post-COVID cohorts participating in WIL and securing job offers at higher rates than in the pre-COVID and COVID eras. We believe these findings could be related, at least in part, to the increase in remote WIL and job opportunities; increased quality in those experiences, especially for minoritized students; and increased value for WIL experiences in securing a job after college. We hope to continue to explore these relationships and other findings at the institution; we also hope that the structure and findings of this study may be informative for other higher education practitioners and researchers.

APPENDIX A. SURVEY QUESTIONS

Your “primary plan” is the ONE post-college activity that will be your focus after graduation. If you plan to do more than one of the activities below, you will have an opportunity to share that information later in the survey.

Please select the statement which MOST CLOSELY describes your PRIMARY plan IMMEDIATELY after graduation.

- Employment (seeking, applying or secured, full-time or part-time, internship, paid or unpaid) (1)
- Continuing education (applying or admitted to graduate school, professional school, or other post-college education) (2)
- Military service (3)
- Volunteering (e.g. AmeriCorps, community service, etc.) (4)
- Starting or raising a family (5)
- Taking time off (6)

Which statement best describes your current employment status?

- Have accepted a position to begin in the coming months (including residency and internship positions) (1)
- Working in a position I plan to continue after graduation (7)
- Have been offered a position or multiple positions, but declined offers and still searching for preferred position (2)
- Considering one or more offers (4)
- Searching or waiting on offers (5)
- Will begin searching for a position in the coming months (6)

The survey will now present you with a series of questions about any internships or other forms of experiential learning in which you may have participated. Please indicate your participation by checking the boxes next to the activities listed.

Internships & Experiential Learning

Check the activities in which you were engaged during your time at [Redacted]. (Select all that apply.)

- Internship
- Cooperative education (co-op)
- Practica
- Field Work
- Student Teaching
- Apprenticeship
- Clinical
- Leadership
- Fellowship
- Other ________________________________
- None of the above

APPENDIX B. SELECTED REGRESSION ANALYSES

Table B1. Logistic Regression Analysis of Securing a Job Offer by COVID Era (Pre-COVID as Reference Group)

Job Offer (*n* = 18,701)	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
COVID eras					
COVID	.827*	.033	.000	.764	.895
Post-COVID	1.08	.044	.053	.999	1.17
WIL	.868*	.031	.000	.809	.930
First generation	.908*	.038	.020	.838	.985
Pell eligible	.916*	.040	.047	.841	.999
URM	.852*	.031	.000	.792	.915
Male	1.02	.035	.661	.948	1.09
Cumulative GPA	1.32*	.054	.000	1.22	1.43

*$p < .05$. OR = odds ratio, SE = standard error.

Table B2. Logistic Regression Analysis of Securing a Job Offer by COVID Era with WIL Participation Interaction (Pre-COVID as reference group)

Job Offer (*n* = 18,701)	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
COVID eras					
COVID	.665*	.045	.000	.583	.759
Post-COVID	.474*	.032	.000	.415	.542
WIL	.553*	.300	.000	.497	.615
COVID era × WIL					
COVID × WIL	1.44*	.120	.000	1.22	1.69
Post-COVID × WIL	3.54*	.300	.000	3.00	4.18
First generation	.911*	.038	.026	.840	.989
Pell eligible	.911*	.040	.034	.835	.993
URM	.840*	.031	.000	.781	.904
Male	1.01	.036	.714	.946	1.09
Cumulative GPA	1.30*	.053	.000	1.20	1.40

*$p < .05$. OR = odds ratio, SE = standard error.

Table B3. Logistic Regression Analysis of Securing a Job Offer within COVID Era

Job Offer	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
Pre-COVID (*n* = 7,867)					
WIL	.541*	.030	.000	.486	.603
First generation	.861*	.056	.021	.759	.978
Pell eligible	.869*	.060	.042	.760	.995
URM	.868*	.051	.015	.774	.973
Male	.983	.054	.748	.883	1.09
Cumulative GPA	1.51*	.094	.000	1.34	1.71
COVID (*n* = 5,150)					
WIL	.800*	.052	.001	.704	.908
First generation	1.00	.077	.999	.860	1.16
Pell eligible	.935	.075	.405	.799	1.09
URM	.762*	.052	.000	.668	.870
Male	1.00	.064	.950	.885	1.14
Cumulative GPA	1.28*	.096	.001	1.10	1.48
Post-COVID (*n* = 5,684)					
WIL	2.05*	.136	.000	1.79	2.33
First generation	.889	.069	.127	.764	1.03
Pell eligible	.939	.078	.452	.798	1.11
URM	.874*	.060	.049	.763	.999
Male	1.07	.071	.286	.943	1.22
Cumulative GPA	1.03	.082	.667	.886	1.21

*$p < .05$. OR = odds ratio, SE = standard error.

Table B4. Logistic Regression Analysis of Securing a Job Offer with First-Generation Status Interaction within COVID Era

Job Offer	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
Pre-COVID (*n* = 7,867)					
WIL	.549*	.035	.000	.485	.623
First generation	.892	.089	.250	.733	1.08
WIL × First generation	.945	.116	.645	.743	1.20
Pell eligible	.870*	.060	.043	.760	.996
URM	.868*	.051	.015	.774	.973
Male	.983	.054	.758	.884	1.09
Cumulative GPA	1.51*	.094	.000	1.34	1.71
COVID (*n* = 5,150)					
WIL	.779*	.060	.001	.669	.907
First generation	.948	.110	.643	.755	1.19
WIL × First generation	1.09	.153	.536	.829	1.43
Pell eligible	.936	.075	.408	.799	1.10
URM	.762*	.052	.000	.668	.871
Male	1.00	.064	.954	.885	1.14
Cumulative GPA	1.28*	.096	.001	1.10	1.48
Post-COVID (*n* = 5,684)					
WIL	2.10*	.166	.000	1.80	2.45
First generation	.939	.110	.594	.747	1.18
WIL × First generation	.914	.130	.528	.691	1.21
Pell eligible	.940	.078	.456	.799	1.11
URM	.875	.060	.052	.765	1.00
Male	1.07	.071	.278	.944	1.22
Cumulative GPA	1.03	.082	.665	.886	1.21

*$p < .05$. OR = odds ratio, SE = standard error.

Table B5. Logistic Regression Analysis of Securing a Job Offer with Pell- eligible Status Interaction within COVID Era

Job Offer	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
Pre-COVID (*n* = 7,867)					
WIL	.568*	.035	.000	.503	.641
Pell eligible	.993	.106	.945	.805	1.22
WIL × Pell eligible	.806	.106	.100	.624	1.04
First generation	.863*	.056	.023	.760	.980
URM	.869*	.051	.016	.775	.974
Male	.985	.054	.778	.885	1.10
Cumulative GPA	1.51*	.094	.000	1.34	1.71
COVID (*n* = 5,150)					
WIL	.786*	.059	.001	.678	.910
Pell eligible	.894	.111	.366	.702	1.14
WIL × Pell eligible	1.07	.159	.635	.803	1.43
First generation	1.00	.077	.988	.861	1.16
URM	.762*	.052	.000	.667	.870
Male	1.00	.064	.951	.885	1.14
Cumulative GPA	1.28*	.096	.001	1.10	1.48
Post-COVID (*n* = 5,684)					
WIL	2.17*	.165	.000	1.87	2.52
Pell eligible	1.10	.143	.465	.853	1.42
WIL × Pell eligible	.783	.120	.112	.580	1.06
First generation	.889	.069	.128	.764	1.03
URM	.872*	.060	.047	.762	.998
Male	1.07	.071	.279	.944	1.22
Cumulative GPA	1.03	.817	.696	.883	1.20

*$p < .05$. OR = odds ratio, SE = standard error.

Table B6. Logistic Regression Analysis of Securing a Job Offer with Underrepresented Racial Minority Status Interaction within COVID Era

Job Offer	OR	SE	*p*-value	95% Confidence Interval	
				Lower	Upper
Pre-COVID (*n* = 7,867)					
WIL	.582*	.039	.000	.511	.664
URM	.995	.092	.957	.830	1.19
WIL × URM	.801	.093	.055	.639	1.00
First generation	.860*	.056	.020	.757	.976
Pell eligible	.871*	.060	.045	.761	.997
Male	.984	.054	.769	.884	1.10
Cumulative GPA	1.51*	.094	.000	1.34	1.71
COVID (*n* = 5,150)					
WIL	.872	.071	.092	.744	1.02
URM	.887	.097	.273	.715	1.10
WIL × URM	.792	.105	.079	.611	1.03
First generation	.997	.077	.972	.858	1.16
Pell eligible	.937	.075	.416	.800	1.10
Male	1.01	.065	.899	.889	1.14
Cumulative GPA	1.28*	.096	.001	1.10	1.48
Post-COVID (*n* = 5,684)					
WIL	2.17*	.183	.000	1.84	2.56
URM	.961	.105	.718	.775	1.19
WIL × URM	.860	.115	.262	.662	1.12
First generation	.892	.069	.140	.767	1.04
Pell eligible	.937	.078	.437	.797	1.10
Male	1.07	.071	.278	.944	1.22
Cumulative GPA	1.03	.082	.673	.885	1.21

*$p < .05$. OR = odds ratio, SE

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