

Using Administrative Data to Support Early Student Success: Predictors of First-Semester Performance in a Puerto Rican Public University

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Abstract

First-semester performance is a practical indicator of students' transition into tertiary education and a point at which institutions can intervene early. This study examined an analytic dataset of 2,048 incoming students admitted to 10 academic programs in the College of Business Administration at the University of Puerto Rico, Río Piedras Campus from 2018–2019 to 2022–2023. An exploratory course-level analysis identified courses with high percentages of critical outcomes, particularly in quantitative and general education areas. Nested and cohort-specific regression models examined academic, sociofamilial, demographic, and institutional constructs associated with first-semester grade point average (GPA). Academic background produced the largest improvement in final nested model fit, which explained 28.5% of the adjusted variance in first-semester GPA. High school GPA and verbal aptitude were the most consistent predictors across cohorts. The findings support ethically designed early alert systems that use student-level indicators alongside course-level interventions to strengthen achievement, retention, and equitable student success.

Keywords: Student success; first-year experience; incoming university students; administrative data; retention; higher education; quantitative analysis.

Introduction

Student success in tertiary education is often measured through institutional outcomes such as retention, persistence, progression, completion, and graduation. For students entering university, however, the first semester is a particularly consequential period because academic expectations, assessment practices, belonging, workload, financial pressures, and institutional support structures begin to interact immediately. First-semester grade point average (GPA) should therefore not be interpreted only as an individual achievement score. It can also serve as an institutional signal that reveals whether students are making a successful transition into university study and whether support mechanisms are reaching them early enough.

This article examines early academic success among incoming students in the College of Business Administration at the University of Puerto Rico, Río Piedras Campus (UPRRP), located in Puerto Rico, an unincorporated territory of the United States (U.S.). Puerto Rico's public higher education system operates within U.S. federal structures, including Pell Grant



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eligibility and Free Application for Federal Student Aid (FAFSA)-based dependency determinations, while facing fiscal, demographic, and infrastructural pressures that differ markedly from those of the mainland. The cohorts examined here entered university in the wake of compounded disruption: Hurricanes Irma and María in September 2017, the earthquake sequence that began in December 2019 and continued through 2020, and the COVID-19 pandemic. These consecutive crises severely disrupted educational services and infrastructure across Puerto Rico, with Hurricane María alone resulting in prolonged school closures and the subsequent earthquake sequence producing additional interruptions, particularly in affected communities (Segarra-Alméstica et al., 2022). Each of these events interrupted instruction, damaged school infrastructure, displaced families, and reduced the continuity of academic support at precisely the stage at which these students were completing secondary schooling. The consequences were unevenly distributed, intensifying pre-existing inequalities in preparation, continuity, and access to academic support. Understanding first-semester performance in this setting therefore requires reading cohort differences as historically situated rather than as fluctuations in student quality. At the same time, the study addresses a broader concern for tertiary education internationally: how institutions can use routinely collected administrative data responsibly to identify patterns of risk, locate courses where critical outcomes (final grades of F [Failed], W [Withdrawn], or NP [Non-passed]) are concentrated, and design practical interventions that improve achievement and retention.

The article makes three contributions to the student success literature. First, it reframes first-semester GPA as an observable transition indicator rather than a narrow measure of individual merit. Second, it evaluates the incremental explanatory value of academic, sociofamilial, demographic, and institutional factors using a cohort-based administrative dataset. Third, it places student-level predictors alongside a course-level mapping of failure, withdrawal, and non-passing outcomes. These complementary analyses inform different institutional responses: early support for students and targeted review of courses with concentrated critical outcomes.

Literature Review and Conceptual Framing

Student Success, Transition, and Early Academic Performance

Current scholarship on student success in tertiary education is often organized around the intersecting themes of Students, Transitions, Achievement, Retention, and Success (STARS), a framework that foregrounds the transition (Nelson & Clarke, 2015). This orientation is useful for interpreting first-semester performance because academic outcomes emerge from a transition process rather than isolated student attributes. Research on student persistence has long emphasized that students' academic and social experiences after entry shape their continuation in tertiary education (Tinto, 1997). More recent work similarly shows that success is multidimensional and cannot be reduced to grades alone; it is associated with self-efficacy, engagement, belonging, social class, expectations, and institutional conditions (Naylor et al., 2026; Pham et al., 2025).

Administrative records and learning analytics can help institutions detect academic difficulty and generate information for student support and institutional decision-making. Their value, however, depends on transparent, fair, and responsible uses of student data (Slade & Prinsloo, 2013). Although these records cannot capture the full student experience, they can reveal observable patterns in academic progression and course outcomes that indicate where advising, academic support, or pedagogical attention may be needed.

Compounded Disruption in the Puerto Rican Context

Puerto Rico offers a case in which the transition into higher education was shaped by a sequence of overlapping shocks rather than a single disruption. Hurricanes Irma and María struck in September 2017, causing extensive damage to educational infrastructure and accelerating a decline in public school enrolment that had already been underway for decades (Nelson et al., 2020). The earthquake sequence that began in December 2019 closed schools across the southern region, and the COVID-19 pandemic followed within weeks of the return to in-person instruction. Segarra-Alméstica et al. (2022) find that these consecutive disasters were associated with measurable declines in students' educational outcomes, and that the disruption of school services was distributed unevenly across the island.

These disruptions were not confined to the K-12 pipeline. Public higher education in Puerto Rico absorbed them while undergoing fiscal contraction and tuition increases, and Segarra-Alméstica and Caraballo-Cueto (2026) show that disasters amplified the negative association between tuition increases and enrolment at both undergraduate and graduate levels. Others have documented the trajectories of Puerto Rican undergraduates displaced to mainland institutions after Hurricane María (Garcia & Danek, 2023). For UPRRP, this history matters directly: the five entering cohorts examined below (2018–2019 to

2022–2023) span the immediate post-hurricane period, the earthquake and pandemic years, and the first post-pandemic cohort, whose members completed most of their secondary schooling under emergency conditions.

Consistent with this, research in Puerto Rico has documented deficiencies in fundamental competencies and difficulties in the transition to university study, particularly during the first academic semesters (Segarra-Alméstica, 2020). Recent work has identified the impact of socioeconomic conditions and educational background on university academic success (Vélez-Ramos et al., 2024). What remains limited is empirical research that systematically analyzes how academic, sociofamilial, demographic, and institutional factors relate to early student performance in specific university populations and reads those relationships against the disruption history of the cohorts concerned.

Academic Preparation and Momentum

Prior academic achievement is consistently associated with performance during the first year of university. High school GPA and standardized assessments often capture accumulated preparation, study habits, and exposure to academic expectations before college entry (Garbanzo Vargas, 2014; Sanchez, 2024). The high school context itself, not only individual prior achievement, can shape first-year college grades (Wolniak & Engberg, 2010). Academic momentum research has further suggested that students' early course-taking patterns, credit accumulation, and first-year outcomes can have consequences for persistence and completion (Attewell & Monaghan, 2016). For quantitatively intensive programs, readiness in mathematics and performance in gateway courses are especially consequential because failure, withdrawal, or delayed enrollment can interrupt momentum early. Research on mathematics pathways, remediation, and the determinants of performance in university mathematics has pointed to both curricular and support-related levers (Mosia et al., 2025; Nunnery & Mathies, 2026; Ran et al., 2025).

Sociofamilial, Demographic, and Institutional Conditions

Student success is also shaped by sociofamilial, demographic, and institutional conditions. Family education, occupational background, economic resources, and emotional support influence students' access to information, time, stability, and encouragement (Jiang et al., 2025; Roksa & Kinsley, 2019), and broader conditions of socioeconomic disadvantage are consistently associated with educational inequality (Silva-Laya et al., 2020). Demographic characteristics are likewise associated with patterned differences in early performance: large-scale evidence indicates that demographic factors carry explanatory information beyond prior achievement, reflecting unequal educational trajectories rather than differences in ability (Jiang et al., 2025; Sanchez, 2024). In Puerto Rico, social and demographic factors have similarly been linked to variation in university performance among business students (Vélez-Ramos et al., 2024). At the institutional level, scholarship receipt and enrollment intensity may affect persistence by shaping financial security, workload, and the capacity to remain engaged in university life (Berlanga & Corti, 2025; Pham et al., 2025), and institutional practices and structures themselves are associated with completion outcomes (de Castro Galvao et al., 2024). These variables must be interpreted ethically. Their value is not to label or stigmatize students but to help institutions understand structural patterns and organize support in ways that are equitable, preventive, and non-punitive.

Taken together, this literature supports a multidimensional transition framework for examining first-semester performance. From this perspective, early academic success is shaped by students' prior preparation and academic momentum, but it is also conditioned by family resources, demographic experiences, institutional structures, and course-level contexts. The four predictor groups used in this study reflect this framework. First, academic background captures accumulated preparation before entry. Second, sociofamilial context represents forms of family, economic, and educational support. Third, demographic characteristics help identify patterned differences in students' educational pathways. Fourth, institutional conditions capture program, enrollment, and financial aid structures that may shape students' transition into university study.

Although prior research has examined predictors of university performance, fewer studies have brought together multiple administrative data sources, cohort-based modeling, and a complementary examination of course-level critical outcomes within the Puerto Rican higher education context. The present study addresses that gap by asking how different academic, sociofamilial, demographic, and institutional factors are associated with first-semester GPA and how these findings, considered alongside course-level critical outcomes, can inform early student success practices.

Research Questions

This study was guided by three research questions: (a) Which academic, sociofamilial, demographic, and institutional variables are associated with first-semester GPA among incoming students? (b) What is the incremental contribution of these groups of variables after accounting for cohort differences? (c) Which courses concentrate high percentages of critical outcomes that may require targeted institutional intervention?

Method

Design and Data Sources

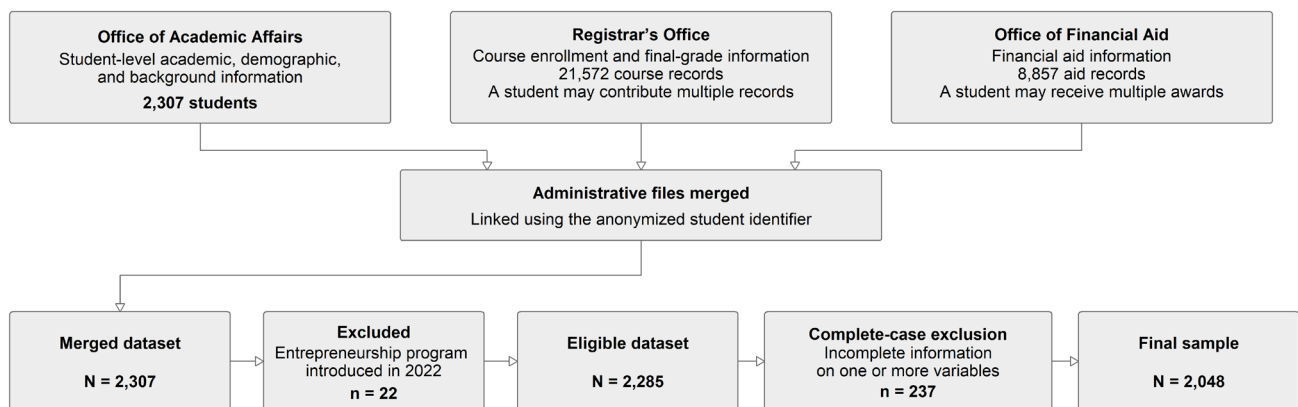
The study used an observational, inferential quantitative design based on administrative records organized by entering cohort. The records corresponded to incoming students admitted between the 2018–2019 and 2022–2023 academic cohorts to 10 academic programs in the College of Business Administration at UPRRP. Records were consolidated from the Office of Academic Affairs, the Office of Financial Aid, and the Registrar's Office. The analytic sample comprised 2,048 incoming students distributed across five entering cohorts: 2018–2019 ($n = 432$), 2019–2020 ($n = 423$), 2020–2021 ($n = 410$), 2021–2022 ($n = 425$), and 2022–2023 ($n = 358$). Table A1 (see Appendix) presents the characteristics of the analytic sample separately for each entering cohort and for the total sample.

Data Management

Administrative records were obtained from the Office of Academic Affairs, the Registrar's Office, and the Office of Financial Aid. The Office of Academic Affairs provided the student-level base file, the Registrar's Office provided course enrollment and final grade records, and the Office of Financial Aid provided aid records, with multiple records possible per student in the latter two sources. The files were linked using an anonymized student identifier, restricted to programs represented throughout the study period, and subjected to complete-case selection for the final model variables. Figure 1 summarizes the sources, linkage process, exclusions, and final analytic sample.

Figure 1

Construction of the Student-Level Analytic Sample



Variables and Coding

First-semester GPA was the dependent variable and was measured on a 0.00–4.00 scale, with 0.00 representing a valid lower-bound value on the same GPA continuum. According to institutional GPA coding, a GPA of 0.00 is a registrar-calculated value reflecting failing performance in GPA-bearing coursework rather than an administrative code for missing or undefined GPA. Predictors were organized into four conceptually defined groups: academic background, sociofamilial context, demographic characteristics, and institutional conditions. Tables A2 and A3 (see Appendix) provide the complete list of variables, their theoretical rationales, types, structures, and observed ranges.

Categorical predictors were represented through dummy or indicator variables using institutional categories as recorded in the administrative files. The reference levels used to interpret the findings were female students for *sex*, Puerto Rico-born students for *country of birth*, San Juan for *educational region*, public school for *school type*, General Business Administration for *academic program*, non-recipient status for *scholarship receipt*, and full-time enrollment for *enrollment status*. This coding strategy makes the results interpretable for institutional planning while avoiding the construction of an unvalidated composite index.

Course-Level Critical Outcomes

In addition to student-level modeling, the study examined first-year course outcomes. *Critical outcomes* were defined as final grades of F, W, or NP. To support stable comparisons, only courses present across all cohorts and with at least 100 cumulative student records were included. Courses with overall critical outcome percentages of 20% or higher were flagged as potential targets for institutional review and support.

Analytical Strategy

Descriptive analyses summarized student characteristics, *first-semester GPA*, and course-level outcomes across cohorts and academic programs. Course-level critical outcomes were examined descriptively as the percentage of final grades of F, W, or NP among courses meeting the inclusion criteria. Cumulative enrollments, numbers of critical outcomes, overall percentages, and 95% confidence intervals were reported to support cautious interpretation of course-level patterns.

Preliminary associations were examined according to variable type. Pearson correlations were used for numerical variables, Cramér's V for associations among categorical variables, and eta squared to estimate the proportion of *first-semester GPA* variance associated with each categorical predictor. The main multivariable analysis used nested regression models with *first-semester GPA* as the dependent variable. Predictor blocks were entered sequentially according to the study framework: cohort, academic background, sociofamilial context, demographic characteristics, and institutional conditions. Cohort-specific regression models were estimated to assess the temporal stability of predictors across pandemic and post-pandemic cohorts. Collinearity was assessed using variance inflation factors. Diagnostic checks for the final nested model included heteroscedasticity assessment, model specification, and influential observations, with HC3 heteroscedasticity-consistent standard errors used for inference. As a bounded-outcome sensitivity analysis, Model 5 was also re-estimated using fractional logistic regression with HC3 standard errors after scaling *first-semester GPA* to the 0–1 interval.

Ethical Considerations

The study used anonymized administrative records, and the protocol was reviewed and approved by the Institutional Committee for the Protection of Human Subjects in Research (CIPSHI) at UPRRP (Protocol #2324-010). Findings based on demographic or sociofamilial variables are presented for equity-oriented planning only and should not be used for punitive decisions, exclusionary screening, or deficit-based labeling of students. The ethical premise of the analysis is that data should trigger support, not surveillance or restriction.

Results

Sample and First-Semester Performance

Table A1 (see Appendix) presents the academic, sociofamilial, demographic, and institutional characteristics of the analytic sample by entering cohort and for the full sample. Across the full analytic sample, *first-semester GPA* ranged from 0.00 to 4.00 ($M = 2.57$, $SD = 1.11$; $Mdn = 2.80$, $IQR = 2.00\text{--}3.40$). Of the 2,048 students, 145 (7.1%) had a *first-semester GPA* of 0.00 and 143 (7.0%) had a GPA of 4.00. The cohorts were broadly comparable in size, although the 2022–2023 cohort was somewhat smaller. *First-semester GPA* varied more across cohorts than *high school GPA*, which remained comparatively stable. *Mathematics aptitude test* and *verbal aptitude test* scores showed a general downward pattern over the study period. The sociofamilial, demographic, and institutional characteristics showed both continuity and selected changes across cohorts, particularly in *school type*, *scholarship receipt*, and *dependency status*.

Table 1 below shows variation by academic program and cohort, including higher mean GPAs in several programs during 2020–2021. Because this cohort coincided with remote instruction and pandemic-related institutional flexibility, these values are interpreted as contextual signals rather than evidence of uniformly stronger preparation.

Table 1

Average First-Semester GPA by Academic Program and Cohort

Academic program	Cohort				
	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023
Accounting	2.63	2.59	2.90	2.53	2.42
Economics	2.61	2.25	2.53	2.16	1.13
Applied Statistics	1.75	2.88	2.83	2.21	2.48
Finance	2.36	2.46	2.93	2.66	2.80
Office Systems Administration	2.60	3.06	2.84	1.98	2.63
Marketing Management	2.71	2.61	2.77	3.04	2.50
Operations and Supply Chain Management	2.70	2.08	3.13	2.35	2.31
Human Resource Management	2.64	2.35	3.13	2.69	2.16
General Business Administration	2.62	2.59	2.80	2.14	2.01
Computer Information Systems	2.80	1.93	2.84	2.26	1.32

Courses with High Percentages of Critical Outcomes

This subsection addresses research question (c) by identifying the courses with high percentages of critical outcomes. Seven courses had overall critical outcome rates of at least 20%. Table 2 shows, for each course, the total enrollment (N), total number of critical outcomes (n), overall percentage with 95% confidence interval, and cohort-specific critical outcome percentages. MATE3001 and MECU3031 were among the courses with the highest overall rates and showed particularly large increases in 2022–2023. Wider confidence intervals for courses with smaller total enrollments, such as CIBI3026, suggest that these overall percentages should be interpreted with greater caution. These results indicate that courses with persistently high or increasing critical outcome rates warrant institutional review alongside student-level support efforts.

Table 2

Courses With Overall Critical Outcome Rates of 20% or Higher

Course	Total (N)	Critical outcomes (n)	Overall % [95% CI]	Cohort				
				2018– 2019	2019– 2020	2020– 2021	2021– 2022	2022– 2023
MATE3001	228	64	28.07 [22.64, 34.23]	10.53	20.00	6.25	11.11	47.12
MECU3031	1332	370	27.78 [25.44, 30.24]	11.11	21.35	16.12	28.38	44.07
SICI3211	351	95	27.07 [22.68, 31.94]	35.00	27.66	21.14	33.33	16.67
HUMA3101	436	103	23.62 [19.88, 27.83]	14.58	20.18	15.15	33.01	27.62
ESPA3003	327	76	23.24 [18.99, 28.11]	0.00	14.71	9.88	31.71	39.66
CONT3105	1703	360	21.14 [19.27, 23.14]	21.87	20.86	16.87	16.72	29.28
CIBI3026	103	21	20.39 [13.74, 29.17]	18.18	0.00	9.68	35.71	25.00

Preliminary Associations

As part of the preliminary analysis of the variables included in the study, possible associations between the predictors and academic success were evaluated, as well as collinearities among variables. In general, the numerical variables showed low correlations with one another ($r < 0.40$), except for the moderate association observed between *mathematics aptitude test* and *verbal aptitude test* scores ($r = 0.52$). In the case of categorical variables, all associations were low ($V < 0.40$). However, a strong association was observed between *dependency status* and *scholarship receipt* ($V = 0.78$); both variables were retained because they capture related but distinct dimensions of financial context, with the former representing dependency classification and the latter institutional aid awarded.

The preliminary analyses showed that categorical predictors generally had small bivariate associations with *first-semester GPA*. *Cohort*, *mother's education*, *sex*, and *father's education* had the highest η^2 values, whereas *educational region*, *country of birth*, and *enrollment status* were not statistically significant. Full results are presented in the Appendix in Table A4.

Nested Regression Models

This subsection addresses research question (b) by quantifying the incremental contribution of each group of predictors after accounting for cohort differences.

As shown in Table 3, the nested models showed a clear pattern. *Cohort* alone made only a limited contribution to the explained variance in *first-semester GPA*, whereas academic background produced by far the largest improvement in model fit. Sociofamilial context, demographic characteristics, and institutional conditions added smaller but statistically detectable increments.

Table 3

Incremental Contribution of Nested Models by Construct

Model	Constructs included	Adjusted R ² (%)	Δ Adjusted R ² (%)	ΔF	df1, df2	p-value (ΔF)
Model 1	Cohort	2.49				
Model 2	+ Academic background	23.27	20.78	199.12	3, 2040	< .001
Model 3	+ Sociofamilial context	25.20	1.93	2.94	29, 2011	< .001
Model 4	+ Demographic characteristics	26.14	0.94	3.43	11, 2000	< .001
Model 5	+ Institutional conditions	28.53	2.39	6.57	12, 1988	< .001

Table A5 (see Appendix) shows the unstandardized regression coefficients, with HC3 heteroscedasticity-consistent standard errors in parentheses. The results show that *high school GPA*, *mathematics aptitude test*, and *verbal aptitude test* remained positively associated with *first-semester GPA* after the successive inclusion of the remaining predictor blocks. *High school GPA* and *verbal aptitude test* were especially stable across Models 2 to 5, indicating that their associations were not substantially altered by adjustment for the other constructs.

In the fully specified model, most parental occupation coefficients and the number of dependents were not statistically significant, while selected parental education categories remained associated with *first-semester GPA*. Male students and students from the Humacao educational region had a lower predicted GPA than their respective reference groups, whereas foreign-born students and students from private schools had a higher predicted GPA. Students in Office Systems Administration, Operations and Supply Chain Management, and Human Resource Management also had a higher predicted GPA than those in General Business Administration, and scholarship recipients had a higher predicted GPA than non-recipients. Enrollment status was not statistically significant after adjustment for the remaining predictors. These results represent conditional associations rather than causal effects. Overall, the final model reached a moderate level of explained variance and is best understood as a tool for early identification and institutional planning rather than deterministic prediction.

Diagnostic and robustness checks for Model 5 supported retaining the ordinary least squares (OLS) specification. The Breusch–Pagan test indicated heteroscedasticity, $\chi^2(59) = 143.41$, $p < .001$, supporting the use of HC3 heteroscedasticity-consistent standard errors. The Ramsey RESET test did not indicate evidence of model misspecification, $F(2, 1986) = 1.44$, $p = .236$. Influence diagnostics identified no observations with a Cook's distance greater than 1 (maximum = 0.077), and all adjusted generalized variance inflation factor (GVIF) values were below 2 (maximum = 1.65), indicating no evidence of problematic multicollinearity among the predictors (O'Brien, 2007). However, the strong association between *dependency status* and *scholarship receipt* may contribute to the instability of the coefficient for the "Not Reported" dependency-status category across Models 4 and 5; therefore, this coefficient should not be interpreted substantively.

As a bounded-outcome sensitivity analysis, *first-semester GPA* was scaled from 0–4 to 0–1 and Model 5 was re-estimated using fractional logistic regression with HC3 standard errors. No coefficient changed statistical significance relative to the

primary OLS model, and all statistically significant predictors retained the same direction. An unconditional random-intercept model also yielded a low intraclass correlation by academic program ($ICC = .019$), indicating that only 1.9% of the variance in *first-semester GPA* was attributable to differences between programs. Taken together, these checks supported retaining the single-level OLS specification with HC3 heteroscedasticity-consistent standard errors.

Cohort-Specific Models

This subsection addresses research question (a) by identifying which academic, sociofamilial, demographic, and institutional variables were associated with *first-semester GPA* in each cohort. The cohort-specific models in Table 4 showed that academic background was the most temporally stable group of predictors. *High school GPA* was significant in all five cohorts and had the largest coefficients among the variables reported. *Verbal aptitude test* was also significant across all cohorts, while the *mathematics aptitude test* was significant in three cohorts. In contrast, *foreign-born* status, *Office Systems Administration*, and *scholarship receipt* were positively associated with *first-semester GPA* in selected cohorts. Specifically, the positive coefficients indicated a higher predicted GPA for foreign-born students compared with students born in Puerto Rico, for students in Office Systems Administration compared with those in General Business Administration, and for scholarship recipients compared with non-recipients, after adjustment for the other variables in the models.

Table 4

Unstandardized Coefficients for Predictors Significant in at Least Two Cohorts

Construct	Predictor	Cohort				
		2018–2019	2019–2020	2020–2021	2021–2022	2022–2023
Academic background	High school GPA	1.04	1.18	0.92	1.81	1.20
	Mathematics aptitude test	0.02	0.02	--	--	0.03
	Verbal aptitude test	0.02	0.03	0.03	0.03	0.02
Demographic characteristics	Foreign-born (Country of birth)	--	0.70	1.06	--	--
Institutional conditions	Office Systems Administration (Academic program)	--	0.97	--	--	1.51
	Scholarship receipt	--	0.95	1.68	--	--

Note. Values are unstandardized coefficients from the cohort-specific models. Dashes indicate non-significant predictors in the corresponding cohort ($p \geq .05$); all listed coefficients are significant at $p < .05$.

These selected associations may reflect differences in subgroup composition, curricular structure, prior preparation, or the eligibility conditions associated with scholarship receipt. However, the small sizes of some subgroups and the limitations of the administrative records do not allow these possible explanations to be distinguished empirically.

Discussion

The findings indicate that early academic success among incoming students is strongly associated with prior academic preparation, but not reducible to it. *High school GPA* and *verbal aptitude test* were the most consistent predictors across cohorts, supporting prior evidence that academic preparation before university remains central to first-year performance (Garbanzo Vargas, 2014; Sanchez, 2024). At the same time, the added explanatory value of sociofamilial, demographic, and institutional variables supports the interpretation that the transition into tertiary education is shaped by multiple conditions.

The models are valuable not as deterministic predictors but as tools for identifying patterns that may guide advising, academic support, curricular review, and further inquiry. Even moderate explanatory power may be institutionally useful when the findings are interpreted cautiously and used to inform supportive interventions rather than to classify students.

The course-level findings are also important because critical outcomes were concentrated in particular quantitative and general education courses. These patterns should not be interpreted solely as evidence of student deficits; they may also reflect

curricular sequencing, assessment design, prerequisite alignment, advising, or the availability of academic support. Consistent with research on gateway courses and academic momentum, the results point to the importance of examining course structures alongside student-level predictors (Mosia et al., 2025; Nunnery & Mathies, 2026; Ran et al., 2025).

The cohort patterns require particular caution. The higher performance observed in 2020–2021, both across several academic programs and in the nested model, should not be interpreted as a straightforward improvement in student preparation; it may reflect emergency remote instruction, institutional flexibility, altered assessment design, withdrawal behavior, or grading practices during an exceptional period. Conversely, several academic programs showed marked declines in 2022–2023: mean *first-semester GPA* fell to 1.13 in Economics and 1.32 in Computer Information Systems, and critical outcome rates rose sharply in courses such as MATE3001 (47.12%), MECU3031 (44.07%), and ESPA3003 (39.66%). Because these later cohorts entered university after the compounded disruption to secondary schooling described earlier (Hurricanes Irma and María, the 2019–2020 earthquake sequence, and the COVID-19 pandemic; Segarra-Alméstica et al., 2022), this pattern may be consistent with interrupted preparation rather than a single-year fluctuation. As with the 2020–2021 results, these movements are best read as contextual signals that warrant institutional inquiry. Treating cohort as both a statistical control and an interpretive context helps avoid misleading comparisons across time.

Implications for Student Success Practice

First, high school GPA and verbal and mathematics aptitude tests can support proactive outreach during the first weeks of the semester. Advising, tutoring, academic planning, and referrals should be offered before students accumulate failing grades. Evidence indicates that multifaceted programs combining advising, mentoring, and tutoring can benefit students, including those from lower-income backgrounds, by connecting them with academic and social support networks (Bowman et al., 2025; Cabrera et al., 2013). These indicators should prompt support conversations rather than labels of ability or motivation.

Second, course-level critical outcome monitoring should become part of regular institutional planning. Courses such as MATE3001 and MECU3031, which showed high critical outcome percentages in 2022–2023, should be reviewed collaboratively by departments, advising units, faculty teams, and student support offices. Possible actions include supplemental instruction, embedded tutoring, early assessments, prerequisite review, and coordination before the withdrawal period. This approach shifts the focus from asking only which students are at risk to asking where the curriculum and support system can be strengthened.

Third, sociofamilial and demographic variables require ethical safeguards because indicators of structural differences in access and preparation can also be used to classify or stigmatize students (Ferguson et al., 2016; Slade & Prinsloo, 2013). The DELICATE framework supports three safeguards (Drachsler & Greller, 2016): purpose limitation, excluding admissions, program access, and disciplinary decisions; transparency and involvement, so students understand the data and may contest inferences; and an obligation to resource appropriate support when risk is identified. These practices should be combined with professional judgment, student participation where appropriate, and periodic equity audits.

Fourth, the College of Business Administration should evaluate the impact of any intervention it implements. If supplemental instruction is added to a gateway course, the college should compare subsequent rates of F, W, and NP outcomes; course completion; credit accumulation; and second-year retention. This may include courses such as MATE3001 or MECU3031, the two courses in which this study found the highest and most sharply increasing concentrations of critical outcomes. This evaluation cycle would connect analytics to evidence-informed action, which is central to a student success agenda.

Limitations and Future Research

Several limitations should guide interpretation. The study examined 10 academic programs in the College of Business Administration at UPRRP, and its cohorts experienced natural disasters, the COVID-19 pandemic, and fiscal contraction. The specific coefficients, demographic associations, and course patterns should therefore not be assumed to apply to other institutions or periods, although the analytic approach of combining student-level indicators, cohort-sensitive interpretation, and course-level monitoring may be adaptable. Administrative records also cannot capture belonging, self-efficacy, engagement, wellbeing, classroom climate, instructional practices, or use of support services. Interviews and focus groups with students, advisors, and faculty, together with replication across campuses and institutions with different missions and populations, would help clarify underlying mechanisms and distinguish context-specific from more broadly observed patterns.

Finally, the observational design supports associations rather than causal conclusions, and cohort differences may partly reflect changes in instructional modality, assessment, advising, grading, or institutional policy. The course-level analysis was descriptive and should be treated as a signal for review, not as evidence of course difficulty, instructional quality, or student ability. Longitudinal and evaluation studies are needed to examine retention; credit accumulation; and the effects of course redesign, supplemental instruction, and early alert interventions.

Conclusion

This study shows that first-semester GPA can serve as a practical indicator of students' transition into tertiary education when interpreted ethically and institutionally. Academic background was the most consistent predictor of early performance, while sociofamilial, demographic, and institutional variables added context. Course-level concentrations of failure, withdrawal, and non-passing outcomes identified areas for institutional review and targeted support. Together, the findings support using administrative data to identify patterns early, respond with support rather than stigma, and pair student-level outreach with course-level improvement. In STARS terms, timely institutional responses connect Students and Transitions with Achievement, Retention, and equitable Success (Nelson & Clarke, 2015).

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Appendix

Table A1

Characteristics of the Analytic Sample by Entering Cohort

Variable	Cohort					Total (N = 2,048)
	2018–2019 (n = 432)	2019–2020 (n = 423)	2020–2021 (n = 410)	2021–2022 (n = 425)	2022–2023 (n = 358)	
Academic Success						
First-Semester GPA	2.61 (0.96)	2.49 (1.05)	2.87 (1.09)	2.53 (1.21)	2.30 (1.18)	2.57 (1.11)
Academic Background						
High School GPA	3.57 (0.36)	3.52 (0.34)	3.58 (0.32)	3.58 (0.33)	3.58 (0.34)	3.56 (0.34)
Mathematics Aptitude Test	547.02 (88.68)	533.39 (87.34)	543.52 (86.13)	522.70 (88.35)	510.72 (86.40)	532.11 (88.32)
Verbal Aptitude Test	544.97 (72.94)	531.39 (69.36)	530.82 (70.45)	510.18 (76.25)	505.78 (75.92)	525.26 (74.31)
Sociofamilial Context						
Mother's Occupation						
Craft, Supervisory, and Repair Occupations	2 (0.5%)	1 (0.2%)	3 (0.7%)	1 (0.2%)	--	7 (0.3%)
Farming, Fishing, and Forestry Occupations	--	--	2 (0.5%)	--	--	2 (0.1%)
Managers and Professionals	144 (33.3%)	140 (33.1%)	122 (29.8%)	126 (29.6%)	96 (26.8%)	628 (30.7%)
Operators, Manufacturing, and Labor Occupations	1 (0.2%)	3 (0.7%)	2 (0.5%)	8 (1.9%)	5 (1.4%)	19 (0.9%)
Technical, Sales, and Administrative Support Occupations	159 (36.8%)	161 (38.1%)	172 (42.0%)	179 (42.1%)	164 (45.8%)	835 (40.8%)
Inactivity	109 (25.2%)	106 (25.1%)	85 (20.7%)	88 (20.7%)	83 (23.2%)	471 (23.0%)
Not Reported	17 (3.9%)	12 (2.8%)	24 (5.9%)	23 (5.4%)	10 (2.8%)	86 (4.2%)
Father's Occupation						
Craft, Supervisory, and Repair Occupations	5 (1.2%)	8 (1.9%)	5 (1.2%)	4 (0.9%)	2 (0.6%)	24 (1.2%)
Farming, Fishing, and Forestry Occupations	2 (0.5%)	1 (0.2%)	1 (0.2%)	2 (0.5%)	3 (0.8%)	9 (0.4%)
Managers and Professionals	121 (28.0%)	117 (27.7%)	95 (23.2%)	113 (26.6%)	97 (27.1%)	543 (26.5%)
Operators, Manufacturing, and Labor Occupations	23 (5.3%)	25 (5.9%)	26 (6.3%)	20 (4.7%)	22 (6.1%)	116 (5.7%)
Technical, Sales, and Administrative Support Occupations	192 (44.4%)	169 (40.0%)	216 (52.7%)	223 (52.5%)	158 (44.1%)	958 (46.8%)
Inactivity	89 (20.6%)	65 (15.4%)	67 (16.3%)	63 (14.8%)	43 (12.0%)	327 (16.0%)
Not Reported	--	38 (9.0%)	--	--	33 (9.2%)	71 (3.5%)

Variable	Cohort					Total (N = 2,048)
	2018–2019 (n = 432)	2019–2020 (n = 423)	2020–2021 (n = 410)	2021–2022 (n = 425)	2022–2023 (n = 358)	
<i>Mother's Education</i>						
No Formal Education	23 (5.3%)	14 (3.3%)	28 (6.8%)	26 (6.1%)	13 (3.6%)	104 (5.1%)
Less Than High School	15 (3.5%)	21 (5.0%)	7 (1.7%)	9 (2.1%)	17 (4.7%)	69 (3.4%)
High School	32 (7.4%)	38 (9.0%)	35 (8.5%)	33 (7.8%)	27 (7.5%)	165 (8.1%)
Some College, No Bachelor's Degree	46 (10.6%)	31 (7.3%)	47 (11.5%)	49 (11.5%)	40 (11.2%)	213 (10.4%)
Bachelor's Degree	178 (41.2%)	181 (42.8%)	180 (43.9%)	175 (41.2%)	135 (37.7%)	849 (41.5%)
Associate Degree	63 (14.6%)	52 (12.3%)	47 (11.5%)	53 (12.5%)	52 (14.5%)	267 (13.0%)
Master's Degree	64 (14.8%)	64 (15.1%)	52 (12.7%)	66 (15.5%)	62 (17.3%)	308 (15.0%)
Doctoral Degree	11 (2.5%)	22 (5.2%)	14 (3.4%)	14 (3.3%)	12 (3.4%)	73 (3.6%)
<i>Father's Education</i>						
No Formal Education	54 (12.5%)	50 (11.8%)	50 (12.2%)	47 (11.1%)	46 (12.8%)	247 (12.1%)
Less Than High School	39 (9.0%)	33 (7.8%)	21 (5.1%)	15 (3.5%)	23 (6.4%)	131 (6.4%)
High School	52 (12.0%)	55 (13.0%)	69 (16.8%)	54 (12.7%)	46 (12.8%)	276 (13.5%)
Some College, No Bachelor's Degree	52 (12.0%)	62 (14.7%)	52 (12.7%)	56 (13.2%)	56 (15.6%)	278 (13.6%)
Bachelor's Degree	126 (29.2%)	119 (28.1%)	125 (30.5%)	135 (31.8%)	111 (31.0%)	616 (30.1%)
Associate Degree	58 (13.4%)	40 (9.5%)	52 (12.7%)	63 (14.8%)	39 (10.9%)	252 (12.3%)
Master's Degree	34 (7.9%)	38 (9.0%)	28 (6.8%)	40 (9.4%)	22 (6.1%)	162 (7.9%)
Doctoral Degree	17 (3.9%)	26 (6.1%)	13 (3.2%)	15 (3.5%)	15 (4.2%)	86 (4.2%)
Number of Dependents within the Family	2.79 (1.53)	2.73 (1.55)	2.59 (1.65)	2.48 (1.55)	2.65 (1.40)	2.65 (1.55)
<i>Dependency Status</i>						
Dependent	400 (92.6%)	388 (91.7%)	372 (90.7%)	389 (91.5%)	312 (87.2%)	1861 (90.9%)
Independent	18 (4.2%)	12 (2.8%)	9 (2.2%)	6 (1.4%)	5 (1.4%)	50 (2.4%)
Not Reported	14 (3.2%)	23 (5.4%)	29 (7.1%)	30 (7.1%)	41 (11.5%)	137 (6.7%)
Demographic Characteristics						
<i>Sex</i>						
Female	190 (44.0%)	177 (41.8%)	182 (44.4%)	192 (45.2%)	157 (43.9%)	898 (43.8%)
Male	242 (56.0%)	246 (58.2%)	228 (55.6%)	233 (54.8%)	201 (56.1%)	1150 (56.2%)
<i>Country of Birth</i>						
Born in Puerto Rico	390 (90.3%)	391 (92.4%)	389 (94.9%)	398 (93.6%)	332 (92.7%)	1900 (92.8%)
Born in the United States	35 (8.1%)	19 (4.5%)	15 (3.7%)	19 (4.5%)	19 (5.3%)	107 (5.2%)
Foreign-Born	7 (1.6%)	13 (3.1%)	6 (1.5%)	8 (1.9%)	7 (2.0%)	41 (2.0%)
<i>Educational Region</i>						
Arecibo	36 (8.3%)	26 (6.1%)	23 (5.6%)	42 (9.9%)	29 (8.1%)	156 (7.6%)
Bayamón	87 (20.1%)	66 (15.6%)	72 (17.6%)	81 (19.1%)	59 (16.5%)	365 (17.8%)

Variable	Cohort					Total (N = 2,048)
	2018–2019 (n = 432)	2019–2020 (n = 423)	2020–2021 (n = 410)	2021–2022 (n = 425)	2022–2023 (n = 358)	
Caguas	43 (10.0%)	51 (12.1%)	46 (11.2%)	51 (12.0%)	58 (16.2%)	249 (12.2%)
Humacao	51 (11.8%)	45 (10.6%)	40 (9.8%)	38 (8.9%)	42 (11.7%)	216 (10.5%)
Mayagüez	2 (0.5%)	1 (0.2%)	1 (0.2%)	3 (0.7%)	4 (1.1%)	11 (0.5%)
Ponce	7 (1.6%)	3 (0.7%)	4 (1.0%)	4 (0.9%)	5 (1.4%)	23 (1.1%)
San Juan	206 (47.7%)	229 (54.1%)	221 (53.9%)	206 (48.5%)	160 (44.7%)	1022 (49.9%)
Outside Puerto Rico	--	2 (0.5%)	3 (0.7%)	--	1 (0.3%)	6 (0.3%)
<i>School Type</i>						
Public School	196 (45.4%)	161 (38.1%)	149 (36.3%)	160 (37.6%)	127 (35.5%)	793 (38.7%)
Private School	236 (54.6%)	262 (61.9%)	261 (63.7%)	265 (62.4%)	231 (64.5%)	1255 (61.3%)
Institutional Conditions						
<i>Academic Program</i>						
Accounting	142 (32.9%)	150 (35.5%)	143 (34.9%)	131 (30.8%)	116 (32.4%)	682 (33.3%)
Applied Statistics	3 (0.7%)	6 (1.4%)	7 (1.7%)	7 (1.6%)	5 (1.4%)	28 (1.4%)
Computer Information Systems	30 (6.9%)	35 (8.3%)	26 (6.3%)	31 (7.3%)	25 (7.0%)	147 (7.2%)
Economics	20 (4.6%)	20 (4.7%)	23 (5.6%)	11 (2.6%)	11 (3.1%)	85 (4.2%)
Finance	53 (12.3%)	50 (11.8%)	51 (12.4%)	63 (14.8%)	48 (13.4%)	265 (12.9%)
General Business Administration	56 (13.0%)	44 (10.4%)	48 (11.7%)	58 (13.6%)	47 (13.1%)	253 (12.4%)
Human Resource Management	23 (5.3%)	30 (7.1%)	32 (7.8%)	34 (8.0%)	19 (5.3%)	138 (6.7%)
Marketing Management	58 (13.4%)	53 (12.5%)	55 (13.4%)	64 (15.1%)	55 (15.4%)	285 (13.9%)
Office Systems Administration	26 (6.0%)	16 (3.8%)	12 (2.9%)	5 (1.2%)	10 (2.8%)	69 (3.4%)
Operations and Supply Chain Management	21 (4.9%)	19 (4.5%)	13 (3.2%)	21 (4.9%)	22 (6.1%)	96 (4.7%)
<i>Scholarship Receipt</i>						
Non-Recipient	36 (8.3%)	35 (8.3%)	45 (11.0%)	34 (8.0%)	71 (19.8%)	221 (10.8%)
Recipient	396 (91.7%)	388 (91.7%)	365 (89.0%)	391 (92.0%)	287 (80.2%)	1827 (89.2%)
<i>Enrollment Status</i>						
Part-Time	11 (2.5%)	3 (0.7%)	7 (1.7%)	17 (4.0%)	12 (3.4%)	50 (2.4%)
Full-Time	412 (95.4%)	405 (95.7%)	395 (96.3%)	407 (95.8%)	343 (95.8%)	1962 (95.8%)
Total Withdrawal	9 (2.1%)	15 (3.5%)	8 (2.0%)	1 (0.2%)	3 (0.8%)	36 (1.8%)

Note. Values are M (SD) for continuous variables and n (%) for categorical variables. Percentages are calculated within each entering cohort. Dashes indicate that no students were observed in that category for the corresponding cohort.

Table A2*Variables, Constructs, and Theoretical Rationale of the Study*

Variable	Construct	Theoretical rationale
First-Semester GPA	Academic Success (Dependent Variable)	Indicator commonly used to evaluate early academic performance in higher education (Garbanzo Vargas, 2014).
Cohort	Control Variable	Captures temporal variation across entering cohorts and institutional contexts (de Castro Galvao et al., 2024).
High School GPA	Academic Background	Prior academic achievement strongly predicts first-year university performance and student success (Sanchez, 2024).
Mathematics Aptitude Test		Mathematics readiness and standardized preparation indicators have been associated with first-year academic performance, particularly in quantitatively intensive pathways (Mosia et al., 2025; Sanchez, 2024).
Verbal Aptitude Test		Verbal aptitude and communication skills are associated with academic adaptation and early student success in higher education (Pham et al., 2025).
Mother's Occupation		Family socioeconomic and support conditions are associated with access to information, stability, and resources that may influence academic performance and persistence (Jiang et al., 2025; Roksa & Kinsley, 2019).
Father's Occupation	Sociofamilial Context	Parental occupational background may reflect differences in economic and social resources that shape students' educational opportunities and academic trajectories (Jiang et al., 2025; Silva-Laya et al., 2020).
Mother's Education		Parental education has been consistently associated with academic adaptation and student retention in higher education (Jiang et al., 2025).
Father's Education		Parental education is linked to academic support and stronger student performance (Jiang et al., 2025).
Number of Dependents		The number of dependents within the family may reflect household resource distribution and the availability of economic and academic support during university studies (Pham et al., 2025).
Dependency Status		Financial dependency status may influence access to family support and economic resources associated with academic persistence and student success (Jiang et al., 2025).
Sex	Demographic Characteristics	Demographic characteristics, including sex, have been considered alongside prior academic indicators in studies of college academic performance and student success (Sanchez, 2024).
Country of Birth		Migration background and cultural adaptation may influence academic integration and performance (Silva-Laya et al., 2020).
Educational Region		Educational context and school background can shape academic preparation before college entry and contribute to differences in first-year performance (Silva-Laya et al., 2020).
School Type		Differences in school context, resources, and educational opportunities may influence students' preparation for tertiary education and subsequent academic performance (Silva-Laya et al., 2020).
Academic Program	Institutional Conditions	Academic programs differ in curricular structure, demands, and performance patterns (Garbanzo Vargas, 2014).
Scholarship Receipt		Financial aid and scholarship programs have been associated with academic performance, continuity, and student success in higher education (Berlanga & Corti, 2025).
Enrollment Status		Academic enrollment intensity may influence student engagement, workload management, and academic performance during the first university year (Pham et al., 2025).

Table A3*Type and Structure of the Variables Included in the Study*

Variable	Type of variable	Structure
First-Semester GPA	Continuous numerical	Scale from 0.00 to 4.00.
Cohort	Categorical temporal variable	Five entering cohorts defined by academic year.
High School GPA	Continuous numerical	Observed range from 2.25 to 4.00.
Mathematics Aptitude Test	Continuous numerical	Observed range from 257 to 800.
Verbal Aptitude Test	Continuous numerical	Observed range from 296 to 745.
Mother's Occupation	Nominal categorical	Seven occupational categories reported.
Father's Occupation	Nominal categorical	Seven occupational categories reported.
Mother's Education	Ordinal categorical	Eight educational attainment categories reported.
Father's Education	Ordinal categorical	Eight educational attainment categories reported.
Number of Dependents	Discrete numerical	Count ranging from 0 to 11.
Dependency Status	Nominal categorical	Three-level classification: dependent, independent, or not reported.
Sex	Binary	Two-level classification: female or male.
Country of Birth	Nominal categorical	Three-level classification: Puerto Rico, United States, or foreign country.
Educational Region	Nominal categorical	Eight official educational region categories reported.
School Type	Binary	Two-level classification: private or public.
Academic Program	Nominal categorical	Ten academic program categories reported.
Scholarship Receipt	Binary	Two-level classification: scholarship recipient or non-recipient.
Enrollment Status	Nominal categorical	Three-level classification: full-time, part-time, or total withdrawal.

Table A4*Bivariate Variance in First-Semester GPA Associated with Categorical Variables*

Variable	Variance (η^2 , %)	p-value	Variable	Variance (η^2 , %)	p-value
Cohort	2.68	< .001	Mother's occupation	0.80	.011
Mother's education	2.59	< .001	School type	0.47	.002
Sex	2.02	< .001	Academic program	0.45	.003
Father's education	1.97	< .001	Educational region	0.39	.341
Scholarship receipt	1.14	< .001	Country of birth	0.21	.121
Father's occupation	1.11	< .001	Enrollment status	0.02	.846
Dependency status	1.05	< .001			

Note. Values are bivariate eta squared (η^2) estimates expressed as percentages. These associations were not adjusted for multiple comparisons and do not represent the unique contribution of each variable in a multivariable model; they are interpreted as preliminary descriptive indicators.

Table A5

Parameter Estimates from Nested Regression Models Predicting First-Semester GPA Using HC3 Robust Standard Errors

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5 95% CI
Intercept	2.612*** (0.046)	-3.740*** (0.267)	-3.490*** (0.318)	-3.255*** (0.334)	-4.550*** (0.361)	[-5.258, -3.842]
Cohort (reference: 2018–2019)						
2019–2020	-0.126 (0.069)	-0.021 (0.061)	-0.031 (0.062)	-0.048 (0.062)	-0.038 (0.061)	[-0.158, 0.082]
2020–2021	0.261*** (0.071)	0.284*** (0.067)	0.287*** (0.067)	0.270*** (0.068)	0.289*** (0.067)	[0.158, 0.420]
2021–2022	-0.077 (0.075)	0.031 (0.066)	0.004 (0.067)	-0.009 (0.068)	0.010 (0.068)	[-0.123, 0.142]
2022–2023	-0.312*** (0.078)	-0.180** (0.069)	-0.183* (0.071)	-0.184* (0.072)	-0.126 (0.072)	[-0.268, 0.015]
Academic Background						
High School GPA		1.194*** (0.065)	1.188*** (0.066)	1.159*** (0.069)	1.225*** (0.069)	[1.090, 1.360]
Mathematics Aptitude Test		0.001*** (0.000)	0.001* (0.000)	0.001* (0.000)	0.001*** (0.000)	[0.000, 0.002]
Verbal Aptitude Test		0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	0.003*** (0.000)	[0.002, 0.003]
Sociofamilial Context						
<i>Mother's Occupation (reference: Inactivity)</i>						
Craft, Supervisory, and Repair Occupations			0.220 (0.295)	0.202 (0.292)	0.166 (0.280)	[-0.383, 0.716]
Farming, Fishing, and Forestry Occupations			-0.720 (2.305)	-0.751 (2.292)	-0.406 (2.001)	[-4.330, 3.519]
Managers and Professionals			0.038 (0.068)	0.038 (0.068)	0.035 (0.068)	[-0.098, 0.168]
Operators, Manufacturing, and Labor Occupations			0.105 (0.211)	0.113 (0.213)	0.095 (0.210)	[-0.317, 0.507]
Technical, Sales, and Administrative Support Occupations			0.008 (0.061)	0.004 (0.061)	0.008 (0.061)	[-0.111, 0.128]
Not Reported			0.079 (0.198)	0.084 (0.196)	0.123 (0.180)	[-0.230, 0.475]
<i>Father's Occupation (reference: Inactivity)</i>						
Craft, Supervisory, and Repair Occupations			-0.070 (0.206)	-0.096 (0.206)	-0.130 (0.209)	[-0.539, 0.279]
Farming, Fishing, and Forestry Occupations			-0.466 (0.369)	-0.420 (0.369)	-0.435 (0.357)	[-1.136, 0.265]
Managers and Professionals			0.099 (0.077)	0.098 (0.077)	0.109 (0.076)	[-0.041, 0.258]
Operators, Manufacturing, and Labor Occupations			0.009 (0.107)	0.040 (0.106)	0.038 (0.108)	[-0.174, 0.250]
Technical, Sales, and Administrative Support Occupations			0.097 (0.069)	0.102 (0.069)	0.089 (0.068)	[-0.045, 0.222]
Not Reported			0.060 (0.146)	0.057 (0.147)	0.059 (0.145)	[-0.225, 0.343]
<i>Mother's Education (reference: No Formal Education)</i>						
Less Than High School			-0.229 (0.219)	-0.276 (0.216)	-0.254 (0.206)	[-0.657, 0.150]
High School			-0.475* (0.201)	-0.473* (0.198)	-0.479** (0.184)	[-0.840, -0.118]

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5 95% CI
Some College, no Bachelor's Degree			-0.148 (0.188)	-0.155 (0.185)	-0.139 (0.171)	[-0.475, 0.197]
Bachelor's Degree			-0.096 (0.180)	-0.086 (0.177)	-0.075 (0.163)	[-0.395, 0.244]
Associate Degree			-0.216 (0.187)	-0.199 (0.185)	-0.185 (0.172)	[-0.521, 0.152]
Master's Degree			-0.125 (0.188)	-0.115 (0.184)	-0.092 (0.172)	[-0.429, 0.245]
Doctoral Degree			0.012 (0.213)	0.033 (0.210)	0.072 (0.198)	[-0.317, 0.460]
<i>Father's Education (reference: No Formal Education)</i>						
Less Than High School			0.265* (0.129)	0.260* (0.129)	0.240 (0.127)	[-0.010, 0.490]
High School			0.034 (0.119)	0.057 (0.119)	0.057 (0.117)	[-0.173, 0.287]
Some College, no Bachelor's Degree			0.202 (0.117)	0.203 (0.117)	0.209 (0.116)	[-0.018, 0.437]
Bachelor's Degree			0.236* (0.112)	0.239* (0.112)	0.241* (0.111)	[0.023, 0.459]
Associate Degree			0.160 (0.117)	0.188 (0.117)	0.202 (0.115)	[-0.024, 0.428]
Master's Degree			0.258* (0.128)	0.238 (0.128)	0.238 (0.127)	[-0.011, 0.488]
Doctoral Degree			0.406** (0.145)	0.387** (0.145)	0.403** (0.144)	[0.120, 0.685]
Number of Dependents Within the Family			-0.011 (0.015)	-0.008 (0.015)	-0.007 (0.015)	[-0.037, 0.023]
<i>Dependency Status (reference: Dependent)</i>						
Independent			-0.250 (0.169)	-0.250 (0.168)	-0.121 (0.158)	[-0.430, 0.188]
Not Reported			-0.250* (0.102)	-0.303** (0.102)	0.219 (0.176)	[-0.127, 0.565]
Demographic Characteristics						
<i>Sex (reference: Female)</i>						
Male				-0.157*** (0.047)	-0.147** (0.048)	[-0.242, -0.052]
<i>Country of Birth (reference: Born in Puerto Rico)</i>						
Born in the United States				0.034 (0.100)	0.044 (0.101)	[-0.154, 0.243]
Foreign-Born				0.462*** (0.113)	0.485*** (0.119)	[0.252, 0.718]
<i>Educational Region (reference: San Juan)</i>						
Arecibo				-0.074 (0.077)	-0.081 (0.077)	[-0.232, 0.070]
Bayamón				-0.072 (0.060)	-0.092 (0.060)	[-0.209, 0.025]
Caguas				-0.132 (0.070)	-0.127 (0.070)	[-0.265, 0.011]
Humacao				-0.178* (0.073)	-0.187** (0.072)	[-0.327, -0.046]
Mayagüez				-0.379 (0.394)	-0.356 (0.390)	[-1.121, 0.408]
Ponce				-0.347 (0.223)	-0.377 (0.215)	[-0.799, 0.045]
Outside Puerto Rico				0.132 (0.177)	-0.021 (0.235)	[-0.482, 0.440]
<i>School Type (reference: Public School)</i>						
Private School				0.089 (0.050)	0.107* (0.050)	[0.008, 0.205]
Institutional Conditions						
<i>Academic Program (reference: General Business Administration)</i>						
Accounting					0.104 (0.075)	[-0.042, 0.250]

Predictor	Model 1	Model 2	Model 3	Model 4	Model 5	Model 5 95% CI
Applied Statistics					0.174 (0.154)	[-0.128, 0.477]
Computer Information Systems					0.169 (0.110)	[-0.047, 0.384]
Economics					0.192 (0.135)	[-0.072, 0.457]
Finance					0.159 (0.090)	[-0.018, 0.335]
Human Resource Management					0.304** (0.102)	[0.105, 0.504]
Marketing Management					0.137 (0.087)	[-0.034, 0.308]
Office Systems Administration					0.793*** (0.126)	[0.546, 1.039]
Operations and Supply Chain Management					0.483*** (0.120)	[0.249, 0.718]
<i>Scholarship Receipt (reference: Non-Recipient)</i>						
Recipient					0.567*** (0.149)	[0.274, 0.860]
<i>Enrollment Status (reference: Full-Time)</i>						
Part-Time					0.024 (0.137)	[-0.246, 0.294]
Total Withdrawal					-0.133 (0.179)	[-0.485, 0.218]

Note. Entries are unstandardized regression coefficients, with HC3 heteroscedasticity-consistent standard errors in parentheses. The final column reports HC3-based 95% confidence intervals for Model 5. Dashes indicate that a predictor was not included in the corresponding model or that the statistic was not applicable. Reference categories are identified in the predictor labels. * $p < .05$. ** $p < .01$. *** $p < .001$.