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Student Conversion: A New Measure and Model for Postsecondary Student Success

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Abstract
Through recent crises in higher education, college and university leaders have renewed their emphasis on student enrollment and retention to strengthen the financial sustainability of their institutions. However, retention studies have not examined the rapid changes in enrollment and corresponding institutional structures that developed since the pandemic. Specifically, there are no retention models that examine the academic success of both on-campus and online students simultaneously or account for student enrollment behaviors beyond graduation or withdrawal. We conducted chi square and classification tree analyses of institutional student records (n = 31,852) from 2013–2024 to understand and predict which residential and online college graduates advance to an additional degree at the same institution, a process we describe as *student conversion*. One-third of students who completed an undergraduate degree at the university later converted to a subsequent degree. The chi-square analysis demonstrates an association between academic discipline and student conversion. The classification tree model predicted student conversion based on modality, sociodemographic factors, and external environment. The classification tree also predicted higher rates of conversion among Black and African American students. The data show student conversion is not a uniform experience; instead, various groups follow different routes to pursue additional degrees at their institution. Our new model of student conversion can help institutional leaders identify targeted support to students who might otherwise miss opportunities for advanced education. These patterns of conversion demonstrate how online coursework creates new advanced study opportunities for non-traditional students who may not follow traditional education pathways.

Keywords Retention · Student success · Classification tree analysis · Enrollment · Online education · Student conversion

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Student Conversion: A New Measure and Model for Postsecondary Student Success

College and university leaders have renewed their emphasis on student enrollment and retention to strengthen the financial sustainability of their institutions and respond to recent crises in higher education (Gansemer-Topf & Schuh, 2025). In the years following the COVID-19 pandemic, most institutions expanded their online offerings and focused on retaining students at both undergraduate and graduate levels of programming (Brown, 2025; Garrett et al., 2023). The widespread increase in online enrollments has resulted in institutions serving two distinct groups of students: on-campus and online. The proliferation of online programming has also created new opportunities for institutions to retain students beyond a single degree or certificate program and welcome back students who previously withdrew from a program. These adaptations to a rapidly changing resource environment bring about a need to understand the extent to which existing models of retention apply (or not) to on-campus *and* online student bodies and to assess new opportunities for student enrollment that have arisen in recent years.

Retention research has long examined interactions between a student's background characteristics and their institution's academic and social systems (Spady, 1970; Tinto, 1975, 1993, 2025). This work has focused on undergraduates and postgraduates, although the latter with much less frequency (Gansemer-Topf et al., 2023; Valencia Quecano et al., 2024). And yet, an important area of student success research that remains overlooked is the bridge students must navigate to successfully advance from the completion of one postsecondary degree to enrollment in a subsequent degree. For example, studies that examine the bridge from undergraduate to graduate study have typically not accounted for where students attend graduate school relative to their undergraduate institution or how institutions may successfully retain students in their transition from one degree to another (Ethington & Smart, 1986; Perna, 2004; English & Umbach, 2016; Xu, 2016).

A concept from customer experience management research known as *conversion* is particularly useful for understanding this period of student progression in ways that promote both institutional revenue generation and student academic success (Lamrhari et al., 2022; Lemon & Verhoef, 2016; Saleem et al., 2019). This expanded view of student success aligns with calls for institutions to view their relationships with students as lifelong rather than ending at graduation or withdrawal (Ackerman & Schibrowsky, 2007). To that end, we integrate retention theory and customer experience management theory and use the term *student conversion* to refer to a student's departure (via graduation or program withdrawal) and return to enrollment at the same institution. For example, student conversion may comprise a graduate's advancement from one credential (e.g., a bachelor's degree) to another (e.g., a graduate degree). This study seeks to describe student conversion opportunities for researchers and institutional leaders by answering the following question: What factors captured by institutional student records are most predictive of student conversion at a hybrid university, and how do these factors manifest in different student groups?

We used a predictive statistical technique known as classification tree analysis to examine student records ($N = 31{,}852$; 2013–2024) at a single university and determine predictors of subsequent degree enrollment among students who received undergraduate degrees at the same institution (Beaulac & Rosenthal, 2019; Worth & Cronin, 2003). Overall, about one-third of students who completed undergraduate degrees at the university later enrolled in another degree program. Academic discipline, racial and ethnic identity, income, parenting status, relationship status, and program modality (i.e., on-campus or online) were all associated with differences in student conversion patterns. The classification tree predicted the highest conversion rates among Black and African American students; however, each branch of the tree exhibited distinct combinations of factors that influenced students' progression from undergraduate completion to subsequent degree enrollment at the university. The data make it clear that student conversion is not a uniform experience, and that various groups may follow different routes in pursuit of additional degrees at their institution.

For colleges and universities that rely on tuition revenue, knowing which students are likely to pursue additional degrees at the same university and how that conversion rate differs for specific groups of students matters. Our findings illustrate how sociodemographic factors, external environment factors, and modality influence students' conversion decisions in complex ways. For example, although Black students were predicted to convert to subsequent degrees at higher rates, the factors that predicted their conversion differed from other subgroups. Furthermore, online coursework emerged as an important factor in student conversion for historically marginalized students. The implications of these nuanced patterns can help institutions target outreach and support efforts to students who might otherwise miss opportunities for advanced education. Our findings also augment existing knowledge of graduate school advancement, demonstrating how online coursework is creating new postsecondary learning opportunities for non-traditional students who may not follow traditional educational pathways. Understanding the factors that influence conversion can help universities more effectively move students across academic levels, increasing the educational opportunities available to both on-campus and online students and deepening relationships with students who already have a pattern of success at the institution.

Literature Review

Scholars have long sought to examine the factors that promote postsecondary student retention and understand how those factors influence student success outcomes (Aljohani, 2016). Thus far, this research has focused on either traditional undergraduates or graduate students (Reason & Braxton, 2023; Valencia Quecano et al., 2024). However, as colleges and universities pursue new enrollment strategies in the face of converging operational crises, institutional leaders and researchers alike need examples of how the scope of existing student retention models can be expanded to (a) recognize the needs of traditional and non-traditional students learning in multiple modalities and (b) explain how and why students may choose to remain loyal to a single institution after departing from that institution via graduation or program withdrawal. This study integrates retention theory and customer experience management theory to highlight an overlooked area in retention research and offer a novel examination of student advancement across the bridge from undergraduate degree completion to enrollment in a subsequent degree within the same institution.

Student Retention, Past and Present

Retention refers to the ability of a college or university to create conditions that encourage students' continued enrollment over a specific period. In prior retention studies, the period assessed is often from the first semester to the next or the first year to the next, but it can also extend to multiple years through degree completion (Aljohani, 2016). Researchers understand retention and degree completion as separate measures of student success; the period during which an institution retains a student may extend over months or years, and yet it may still end before the student completes a certificate or degree (Bowen et al., 2011). Recently, measures of retention have become key performance indicators for institutions seeking to strengthen their financial stability and educational mission (Gansemer-Topf & Schuh, 2025).

Retention scholars have focused their postsecondary research on two distinct groups of students: undergraduates and postgraduates. Undergraduate retention research prioritizes understanding students' reasons for remaining enrolled in a degree program, identifying risk factors for withdrawal, and developing interventions that effectively support student engagement and academic success (Barbera et al., 2020; Burke, 2019). The subjects of this research are most often traditional undergraduates (i.e., full-time students aged 18–24 who are financially dependent on their parents) attending public colleges and universities (Gansemer-Topf et al., 2023). Over 90% of undergraduate retention studies conducted between 2009 and 2019 focused on student characteristics (e.g., socioeconomic status, racial and ethnic identity, enrollment status) and experiences (e.g., interactions with faculty) as primary variables (Gansemer-Topf et al., 2023). Some studies examine first-to-second-year retention (e.g., Jamelske, 2009), while others investigate retention over multiple years or through degree completion, which remains the commonly accepted retention endpoint (e.g., Niu & Tienda, 2013). In contrast, graduate retention studies are less abundant than those on undergraduate retention, likely due to research design challenges presented by greater variability in graduate degree types, levels of study, enrollment patterns, and time to degree completion (Isaac, 1993; Valencia Quecano et al., 2024). The empirical knowledge gained from these two focal areas of retention research—undergraduate and graduate programs—has become particularly important to colleges and universities as they face multiple institutional crises.

Recent systemic strains on higher education have made student retention a critical component of institutional stability. A series of successive crises has challenged the financial state of colleges and universities, including the COVID-19 pandemic, substantial reductions in federal research funding, and the arrival of the demographic "enrollment cliff" (Grawe, 2018; McClure et al., 2020). In addition, shifts in federal and state funding have incentivized colleges and universities to generate additional revenue by recruiting and enrolling more students to obtain "per student" funding (Brown, 2025). The convergence of these multiple challenges, each one quite formidable on its own, will require institutional leaders to refine their enrollment management strategy from a dominant focus on recruiting new students to a shared focus on recruiting *and* retaining existing students to ensure their success. This increased institutional emphasis on student retention coincides with a time when student populations at many colleges and universities are changing.

Since the COVID-19 pandemic, many colleges and universities have strategically recruited large numbers of non-traditional students via adult education and online program offerings. These recruitment efforts stabilized institutional finances, but also substantially diversified student populations and created two different student bodies within a single school: on-campus students, who are predominantly seen, and online students, who are predominantly unseen (Brown et al., 2022). While many institutions have reaped the financial benefits of this enrollment growth, most have yet to figure out how to meet the unique success needs of non-traditional and online learners, as evidenced by these students' substantially lower likelihood of completing degrees as compared to traditional students (Irwin et al., 2024). New models and measures of student success must account for the complexity within individual institutions serving both online and on-campus students to better explain how these schools can equitably support their seen and unseen student populations. Achieving this goal also requires expanding the scope of retention research beyond its prior emphasis on discrete undergraduate and graduate foci.

Crossing the Bridge from One Degree to Another

An important and overlooked area within retention research involves the bridge between the completion of one degree program and a new enrollment in a subsequent program. For example, past research indicates that students are less likely to enroll in a graduate program at the same institution where they earned their undergraduate degree (Kallio, 1995), but this conclusion is based on data collected from a sample of traditional college students. Whether this same pattern exists among non-traditional, online, or 21st-century college students is not yet known.

Recent research on the undergraduate-to-graduate bridge does not account for where students choose to attend graduate school, but it does identify factors that increase their likelihood of attending regardless of location, including financial assistance and past academic achievement (Mattern & Radunzel, 2015; Mullen et al., 2003). This research has also revealed that Black and African American college students are more likely than students of other racial and ethnic identities to aspire to, apply to, and attend graduate school (Perna, 2004; Wolniak et al., 2020). The influence of factors such as gender, age, marital status, parenting status, parents' education, and socioeconomic status on graduate school advancement has been inconsistent across past studies, indicating the need for more research on these relationships (English & Umbach, 2016; Nevill & Chen, 2007; Xu, 2014, 2016; Zhang, 2005). Furthermore, empirical explorations of how students' characteristics and experiences influence their choices to move to a new institution for graduate study or remain at the university where they earned their undergraduate degree are extremely rare (Simeunovic et al., 2024).

Most prior retention studies limit their examinations of continuing enrollment to two consecutive semesters, one year, or up to program completion (Barbera et al., 2020; Gansemer & Topf, 2023). However, examining patterns among graduates enrolling in *new degree or certificate programs at the same institution* (e.g., college graduates enrolling in graduate programs) can offer new insights about student progress over the bridge from one program to another. Adult and online learners, who do not have the same mobility options as traditional undergraduates, often make college enrollment and continuation decisions based on life circumstances (Iloh, 2018; Markle, 2015). As colleges and universities expand their online programming, they also increase opportunities for non-traditional students to continue their education via pathways that traditional students have not often pursued, such as by enrolling at the same institution for a new degree or certificate program after completing a prior program. Exploring the movement of students across the bridge between programs at the same institution allows researchers and institutional leaders to use a new measure of student success and understand what may drive on-campus and online students to remain at the same school while advancing from one program to the next.

Student Conversion: A New Measure of Student Success

An important way to understand student progress across the bridge from one degree or certificate program to another is through the lens of *conversion*, which customer experience management scholars describe as a customer's choice to follow a specific call to action that advances them toward a greater level of engagement with the organization (Lamrhari et al., 2022; Lemon & Verhoef, 2016; Saleem et al., 2019). Examples of conversion include making a purchase or remaining a loyal customer over an extended period. From an institutional perspective, retention is a higher education-specific form of conversion, signifying a student's willingness to continue engaging with the college or university where they are enrolled (Ackerman & Schibrowsky, 2007). However, because retention has long been recognized as occurring within the boundaries of a period of continuous enrollment in a single degree program, we introduce the term *student conversion* to represent a student's return to enrollment at an institution after departing via graduation or program withdrawal. These returning students may enroll in new programs or, in the case of some withdrawn students, re-enroll in a previously suspended program of study. All instances of student conversion represent a deepening of the relationship between a student and an institution that is distinct from retention within a single degree program.

New models of student success must accurately reflect the sudden demographic changes institutions have experienced since the COVID-19 pandemic and incorporate both seen (on-campus) and unseen (online) students (Brown et al., 2022). Only then will college and university leaders be able to apply these models to meet the needs of all students enrolled at their institutions. In the present study, we operationalize *student conversion* as students' advancement from undergraduate completion to a new degree program at the same institution. We use this measure to analyze institutional data representing both online and on-campus students. The conceptual foundation of our study is a newly conceived model of student enrollment at hybrid institutions (see next section) that incorporates the concept of student conversion and describes how students move through institutions serving seen and unseen student populations. Our study empirically examines the following question: What factors captured by institutional student records are most predictive of student conversion at a hybrid university, and how do these factors manifest in different student groups?

Theoretical and Conceptual Foundations of Student Conversion

No existing student success model captures the complexities of student enrollment at hybrid institutions of higher education. While retention models explain how a student's postsecondary enrollment progresses from recruitment through attrition, these models do not address enrollment decisions a student may make after departing from an institution, nor do they account for the effect of modality on a student's enrollment at an institution. However, the customer experience management literature offers a helpful lens for expanding the scope of student progression through postsecondary institutions to include the post-departure period after graduation or withdrawal. We developed a conceptual model of student enrollment at hybrid higher education institutions that integrates existing models of student retention and customer experience management (Lemon & Verhoef, 2016; Saleem et al., 2019; Siebert et al., 2020; Tinto, 1993, 2025) to explain how students move through institutions serving on-campus and online populations via multiple instructional modalities.

In the retention literature, the Institutional Departure Model (Tinto, 1993) describes post-secondary student success as a longitudinal process of student integration into the academic and social systems of an institution. This integration results from a student's ongoing interactions with an institution throughout the student's enrollment, and it informs a student's perceptions about their personal congruence with the norms and values of an institution. A student's background characteristics, educational goals, and commitment to an institution influence their interactions with the institution and their resulting perceptions of congruence. If a student perceives that they "fit in" at the institution, they are more likely to persist in their education and remain at that institution through graduation. However, if a student only minimally interacts with an institution or perceives a lack of congruence with an institution, they are more likely to withdraw prior to graduation. Although the Institutional Departure Model provides a longitudinal explanation of student behaviors, it does not account for a student's enrollment decisions made after departing from an institution via graduation or withdrawal, nor does it recognize how a student's modality may influence the frequency or character of a student's interactions with the academic and social systems of an institution. These limitations, which resemble those of other models of postsecondary student retention (e.g., Spady, 1970; Bean, 1982; Bean & Metzner, 1985), highlight an opportunity to develop an inclusive model of student success that accounts for multiple modalities and pathways to degree completion.

The customer experience management literature offers a path toward an expanded view of student success that can help institutions understand what may motivate students to return after departing. The Process Model for Customer Journey and Experience (Lemon & Verhoef, 2016) describes the customer experience journey as comprising an individual's "cognitive, emotional, behavioral, sensorial, and social responses" (p. 71) to an organization's services and products. The model represents a customer's journey as an iterative, three-stage process comprising pre-purchase, purchase, and post-purchase phases. Customers take specific actions during each phase as they move from choosing an organization to purchase from, to making a purchase, to using the purchased product or service. A customer's past experiences and interactions with the organization inform their perceptions of the organization, which in turn guide their customer journey. Customers who arrive at the post-purchase phase may then enter a loyalty loop: a cyclical pattern of predictable experiences that build customer loyalty over time (Court et al., 2009). Service providers can also take specific actions to encourage a customer to broaden their relationship with the organization and purchase additional, complementary products or services, thereby expanding the customer journey beyond the loyalty loop (Bolton et al., 2004; Siebert et al., 2020). This idea of expanding the customer journey aligns with calls for colleges and universities to view student-institution relationships as lifelong rather than ending at graduation or institutional withdrawal (Ackerman & Schibrowsky, 2007).

The Institutional Departure Model (Tinto, 1993) and the Process Model for the Customer Journey (Lemon & Verhoef, 2016) share six commonalities that facilitate their integration. First, both models operate within a postpositivist paradigm, acknowledging the importance of an objective reality *and* subjective experiences in understanding how individuals make decisions. Second, both models describe their respective phenomena as longitudinal processes. In one model, postsecondary students move through a pre-entry period, initial and ongoing institutional experiences, academic/social integration, and persistence/dropout decision points (Tinto, 1993), whereas in the other model, customers move through pre-purchase, purchase, and post-purchase stages (Lemon & Verhoef, 2016). Third, both models assume that focal outcomes result from dynamic and iterative individual-environmental interactions in which individuals' background characteristics and experiences influence their perceptions and behaviors. Fourth, both models assume an individual's subjective perceptions and experiences represent salient and measurable knowledge as well as valid data sources that contribute to individual decisions. Fifth, both models employ a systems approach to explain their respective phenomena, demonstrating how multiple constructs interact simultaneously and contribute to feedback loops that influence later stages of the process. Finally, both models assume there are identifiable relationships between antecedents, experiences, and outcomes, allowing for the identification of potential interventions to enhance the student-institution or customer-organization relationship. These six shared characteristics serve as the foundation of an integrated conceptual model that captures the reality of student enrollment in today's hybrid postsecondary institutions.

We propose that converging the Institutional Departure Model (Tinto, 1993) and the Process Model for the Customer Journey (Lemon & Verhoef, 2016) enables an expanded view of student success that reflects the financial needs of today's institutions and the diverse institutional experiences of today's postsecondary students. Our integrated conceptual model of student enrollment at hybrid higher education institutions (see Fig. 1) maps a student's journey within an institution through four phases—from pre-matriculation through post-departure—all occurring within larger *economic*, *political*, *and social contexts* that may affect both students and their institutions.

The first phase in a student's journey, the *pre-purchase phase*, identifies the salient factors in a student's *search for* and *consideration of* their options for higher education. In this phase, a student draws upon their background characteristics to help them identify their *educational aspirations*, select an institution that may meet their needs, and develop an initial *commitment to the institution*. The background characteristics that inform these decisions

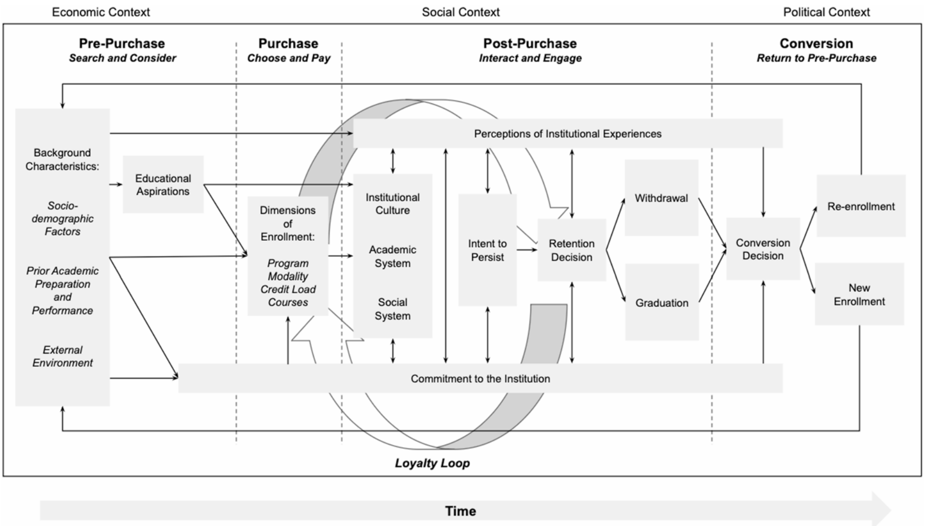


Fig. 1 A conceptual model of student enrollment at hybrid higher education institutions

include *sociodemographic characteristics* (e.g., racial and ethnic identity), *prior academic preparation and performance* (e.g., high school GPA, transfer student status), and *external environment (*e.g., personal relationships, occupational demands).

Once a student identifies an institution that meets their needs, they enter the second phase of their journey, the *purchase phase*, which comprises *choosing* the institution and *paying* to matriculate. At this time, a student also chooses their academic *program* of study, their program *modality* (e.g., on-campus, online, or a mix of both), their *credit load* (full-time or part-time), and their specific *courses*. A student's background characteristics, educational aspirations, and initial *commitment to the institution* all contribute to these decisions, which serve as a filter through which the student will interact with the institution during their enrollment.

The third phase of a student's journey, the *post-purchase phase*, explains how a student *interacts* and *engages* with an institution's *culture* (e.g., policies, practices, and staff), *academic system* (e.g., academic discipline, GPA, and faculty interactions), and *social system* (e.g., formal and informal social opportunities). A student's interactions form a reciprocal relationship with their *perceptions of institutional experiences*, which are informed by the student's background characteristics and interconnected with the student's continued *commitment to the institution*. Each semester, a student makes three decisions—shaped by their perceptions and institutional commitment—to determine their enrollment status for the following term. In this decision-making process, a student first determines whether they *intend to persist* and continue their education regardless of which institution they attend. Next, students who choose to persist make a *retention decision* about whether to remain at their current institution. Finally, students who decide to remain return to the *purchase phase* to select their *program*, *modality*, *credit load*, and *courses*. As signified by the cyclical arrows in the center of the model, students who continue their enrollment at the same institution—and are, therefore, successfully retained by the institution—enter a *loyalty loop*, leading to a new set of institutional experiences in each subsequent term. Students reach the end of the post-purchase phase via one of two pathways: graduation or withdrawal. Students who remain in the loyalty loop until they complete their degree requirements eventually exit an institution via *graduation*. Students who exit the loyalty loop prior to completing their degree requirements *withdraw* from an institution without graduating. Models of student retention focus on phenomena occurring within the first through third phases, whereas our model of student conversion focuses on the fourth phase.

The fourth and final phase of the student journey, the *conversion phase*, represents an opportunity for institutions to sustain relationships with students beyond their departure from a degree or certificate program. Retention models do not recognize this post-departure period as part of a student's journey with an institution. However, this period represents a potential bridge between enrollments during which a continued student-institution relationship may influence a student's future educational decisions. This final phase commences with a student making a *conversion decision* about whether they want to return to the institution from which they departed to continue their education. This decision is informed by a student's prior *commitment to the institution* and prior *perceptions of institutional experiences* before they departed via graduation or withdrawal. If an institution successfully extends the relationship with a student who departed via *graduation*, that individual may choose to return to the pre-purchase phase to begin a *new enrollment*. Alternatively, if an institution extends the relationship with a student who departed via *withdrawal*, that individual may eventually elect to return to the pre-purchase phase to either finish their previously interrupted program via a *re-enrollment* or commence a *new enrollment* in a different program. As our conceptual model demonstrates, both conversion pathways—re-enrollment and new enrollment—present opportunities for institutions to establish new opportunities for academic advancement and success for the students they serve.

Methods

To address our research question, we obtained de-identified student records from a large university in the Eastern United States from 2013 to 2024. The information in the student records was extracted by information technology personnel from the university's centralized student records database. We used these records to determine how various factors predict *student conversion* from an undergraduate degree to enrollment in a subsequent degree.

Data

The records obtained from the university included information for 192,608 undergraduate students enrolled at the institution for at least one semester between 2013 and 2024. We eliminated the records of students who had not graduated as of Spring 2020, which allowed for a minimum of four years for conversion. Additionally, students who transferred in more than 75% of the credits required for their degree were excluded, as were military personnel, who possess unique characteristics relevant to predicting student outcomes (Volk et al., 2020). The final sample included the administrative records of 31,852 students who graduated from their undergraduate program between 2013 and 2020.

The university's academic year consists of fall, spring, and summer terms. The average length of time between students' graduation and their enrollment in a subsequent program was 4.07 terms (SD = 4.55). Just over 93% of students who enrolled in a graduate program did so within four years (12 terms) of completing their bachelor's degree. Of students who converted (n = 10,332), the majority began a master 's-level program (88.9%, n = 9,187). Additionally, 8.4% of students (n = 872) continued into a second undergraduate degree, and the remaining 2.7% (n = 273) continued into a doctoral program. Most students who converted (86.7%) subsequently enrolled in an online program, with only 13.3% enrolling in an on-campus program.

The university had a robust online program prior to the COVID-19 pandemic with largely consistent trends in online and residential enrollment over time, including in the years immediately before and after the COVID-19 pandemic. Students' ages at the completion of their undergraduate program ranged from 15 to 80 years old (M = 29.07, SD = 10.12), their cumulative undergraduate GPA at graduation averaged 3.32 (SD = 0.49), they transferred an average of 42.03 credit hours (SD = 26.65) from other institutions to meet their undergraduate degree requirements, and their median annual household income was $56,335. A summary of additional characteristics of the sample appears in Tables 1 and 2.

As is typical in large databases of information, some administrative student records were incomplete. We labeled information in a student's record as *missing* if their entry for a particular characteristic was empty, indicating that they did not respond to the university's requests for this information, whether intentionally or unintentionally. We labeled an entry

Table 1 Personal characteristics of students

Characteristic	*N*	%
First-generation student		
Yes	9200	28.9
No	17,781	55.8
Missing	4871	15.3
Gender		
Female	19,466	61.1
Male	12,165	38.2
Missing	192	0.6
Other	29	0.1
Pell Grant eligibility		
Eligible	13,462	42.3
Ineligible	13,519	42.4
Missing	4871	15.3
Race/ethnicity		
American Indian/Alaska Native	133	0.4
Asian	437	1.4
Black/African American	2627	8.2
Hispanic/Latino	1432	4.5
Multiracial	709	2.2
Native Hawaiian/Other Pacific Islander	28	0.1
Unreported	6812	21.4
U.S. Nonresident[a]	306	1.0
White	19,368	60.8
U.S. residency status		
Nonresident[b]	341	1.1
Permanent resident	310	1.0
U.S. citizen/national	31,201	98.0

[a] U.S. Nonresident reflects a race/ethnicity response option provided on the FAFSA application for students who are in the United States temporarily, such as on a visa. Separating U.S. Nonresident students from other U.S. students aligns with the U.S. government's current race/ethnicity reporting standards (National Center for Education Statistics, 2025)

[b] The nonresident response option for U.S. residency status is distinct from the race/ethnicity response option U.S. Nonresident (National Center for Education Statistics, 2025). Each of the categories reflects a different number of students

in a student's record as *unreported* if a student responded to a request for this information with an indication that they preferred not to answer. Because the statistical method we selected is designed to handle missing data effectively by treating missing values as a unique subgroup, we retained missing and unreported information in the dataset to maximize the sample size.

Data Analysis

We used chi-square and classification tree analyses to identify relationships between various factors captured by the university's student records and student conversion. We excluded academic year of graduation from our analyses because of its potential to confound the results; students who graduated from college earlier had more time to enroll in a subsequent program and, therefore, may have higher conversion rates than students who graduated more recently.

Table 2 Academic and external characteristics of students

Characteristic	*N*	%
External environment		
Relationship status		
Divorced	1018	3.2
Married	10,051	31.6
Missing	3976	12.5
Separated	388	0.9
Single	16,174	50.8
Unreported	233	0.7
Widowed	112	0.4
Parenting status		
Yes	8471	26.6
No	18,510	58.1
Missing	4871	15.3
Modality		
Program modality		
Online	19,629	61.6
Residential	12,223	38.4
Academic System		
Academic discipline		
Humanities	10,048	31.5
Natural & applied sciences	4053	12.7
Social sciences	17,751	55.7
Academic year of graduation		
2013–2014	3754	11.8
2014–2015	3992	12.5
2015–2016	4294	13.5
2016–2017	4352	13.7
2017–2018	5174	16.2
2018–2019	5174	16.2
2019–2020	5437	17.1

Chi-square Analysis

While academic discipline may influence patterns in student conversion, these patterns may also reflect field-specific postgraduate education norms, degree availability, or curriculum development efforts over time at the university, none of which are the focus of the present study. For this reason, we chose to exclude academic discipline from the larger classification tree analysis. We instead determined whether there is a statistically significant relationship between student conversion and academic discipline using a chi-square test of independence.

Classification Tree Analysis

Classification tree analysis (CTA) is a statistical method for determining the degree to which an array of variables may predict a nominal target outcome, known as the *root node*. In this analysis, the root node is student conversion from undergraduate completion to a new degree program within the same academic institution (0 = not converted, 1 = converted).

The classification tree is constructed from the root node using a data mining algorithm that divides the sample into subgroups by identifying the predictors that optimally differentiate cases based on the outcome variable (i.e., student conversion). These predictors can be categorical (e.g., race/ethnicity) or continuous (e.g., household income). Each subgroup identified by the algorithm is differentiated from the other subgroups based on the percentage of cases in the subgroup that align with the target outcome (student conversion). Visually, each subgroup in the classification tree is represented by a *node*.

The algorithm may further divide a *parent node* into *child nodes* using the same splitting process based on the model predictors. Node generation continues recursively until *terminal nodes* appear or specific conditions, such as a certain tree depth, are met. The resulting hierarchical structure resembles an inverted tree and offers a visual representation that facilitates data interpretation.

CTA is a descriptive statistical technique, producing results that allow for predictive, rather than causal, claims. Compared to logistic regression, which simultaneously analyzes multiple variables to identify the frequency of dichotomous outcomes, CTA analyzes each variable individually and iteratively to identify the strongest predictors across multiple steps (Worth & Cronin, 2003). Particularly for prediction involving personal factors, which are often categorical, classification trees provide an optimal way of combining predictor variables to maximally explain an outcome. Additionally, CTA reconsiders predictor variables for each new subgroup identified by the analysis. Whereas logistic regression requires the removal or imputation of missing data, CTA can flexibly handle missing data and nonlinear relationships to generate a nuanced analysis.

While numerous data mining techniques can be used to grow a classification tree, we employed the chi-square automatic interaction detector (CHAID; Kass, 1980), which considers continuous, nominal, and ordinal data when determining how predictor variables correlate with dichotomous outcomes. CHAID minimizes within-node variance and maximizes between-node variance. The algorithm cross-tabulates predictive variables until the most optimal discriminator is identified, resulting in child nodes based on the strongest predictor of discrimination.

We analyzed the data using SPSS (v 29.0) and ran the entirety of the eligible data through the CHAID algorithm. We set the following criteria for the classification tree: a maximum tree depth of six levels, a significance level of 0.05, a minimum of 100 cases to produce a divisible node, and a minimum of 50 cases to produce a terminal node. The predictive variables included in our analysis appear in Table 3.

Addressing Threats to CTA Model Validity

While machine learning models can provide a thorough description of a sample, they are also susceptible to flawed algorithmic decision-making that may perpetuate existing social biases, such as stereotyping based on identity characteristics (Anglin, 2024). For example, some machine learning model predictions are less accurate when an outcome is more common among people in certain demographic subgroups or when demographic variables act as confounders within predictive analytic models (Bird et al., 2021; Gándara et al., 2024). We therefore took steps to bolster our model's performance and reduce its likelihood of algorithmic bias, consistent with Anglin's (2024) recommendations. First, we constrained predictors to factors that are theoretically relevant to the outcome variable (see Theoreti-

Table 3 Descriptions and response options of variables included in the data analysis

Variable	Description	Response options
Sociodemographic		
Age	Age of a student in the final semester of their undergraduate program	Scale
First-generation student	Designates whether a student is a first-generation college student	Yes, no
Gender	A student's self-reported gender in their final undergraduate semester	Female, male, other
Household income	A student's self-reported household income in their final undergraduate semester	Scale
Pell Grant eligibility	Designates whether a student was eligible to receive the federal Pell Grant as an undergraduate	Yes, no
Race/ethnicity	A student's self-reported race/ethnicity	American Indian/Alaska Native, Asian, Black/African American, Hispanic/Latino, Multiracial, Native Hawaiian/Pacific Islander, U.S. Nonresident, White
U.S. residency status	A student's self-reported U.S. residency status in their final undergraduate semester	Nonresident, permanent resident, U.S. National, U.S. citizen
Prior academic preparation and performance		
Total transfer hours	The number of undergraduate credit hours a student transferred into the university	Scale
External environment		
Relationship status	A student's self-reported relationship status in their final undergraduate semester	Divorced, married, separated, single, widowed
Parenting status	A student's self-reported number of children in their final undergraduate semester	Yes, no
Modality		
Modality	Indicates the delivery mode of a student's undergraduate program	Online, residential
Academic system		
Academic Discipline	Discipline of student in the final semester of their undergraduate program	Humanities, natural & applied sciences, social sciences
Total GPA	A student's cumulative GPA in their undergraduate program	Scale

cal and Conceptual Foundations of Student Conversion). Second, additional analyses were conducted to explore the algorithm's performance across subgroups, providing insight into the fairness of the model (Gándara et al., 2024).

Furthermore, as CTA is prone to overfitting (Anglin, 2024), we used *k*-fold cross-validation to assess the extent to which the predictive performance of our CTA model generalizes to an as-yet-unseen dataset (Hastie et al., 2009). To cross-validate a classification tree, the dataset is subdivided into folds which are sequentially excluded from the generation of the models. For a tree with *k* folds, the model will be trained *k* times, with *k*-1 folds included at a time. Each tree then can be used to predict the fold that is excluded from that tree, from which a misclassification rate can be produced. The tree with the lowest misclassification rate is the optimal cross-validation tree. We specified 10 folds to optimize the generalizability of our model's predictive performance.

Results

The actual rate of student conversion among the students in the sample was 32.4%. The CTA model produced from the dataset predicted student conversion with 70% accuracy. The chi-square and classification tree analyses revealed statistically significant relationships between several predictive factors and student conversion. Our statistical validity analysis revealed differences in the CTA model's performance based on students' racial and ethnic identities.

Chi-square Analysis

The results of the chi-square test of independence were statistically significant ($\chi^2 = 344.94$, $p < 0.001$), suggesting that there is an association between academic discipline and student conversion. However, the overall effect size of this association was small (Cramer's V = 0.104). Specifically, 34.6% of students in the humanities and 34.1% of students in the social sciences continued to another program at the same university after graduation, whereas only 19.7% of students in the natural and applied sciences converted to a subsequent program.

Classification Tree Analysis

The classification tree identified numerous factors that explained differences in predicted conversion rates, including racial and ethnic identity, relationship status, parenting status, annual household income, Pell Grant eligibility, and modality (see Table 4). Racial and ethnic identity was the strongest differentiator in predicted rates of student conversion, partitioning the sample into four groups ($\chi^2 = 932.35$, $p < 0.001$; see Fig. 2), each of which became a unique branch in the tree. For the two largest branches ($n = 21{,}237$; $n = 7146$), the classification tree extended to six levels, while the two smaller branches ($n = 842$; $n = 2627$) extended to three and four levels, respectively.

Four notable findings emerged from our analysis of the classification tree. First, Black and African American students formed a distinctive branch in the tree (branch A; see Table 4; Fig. 2) and converted to new degree programs at higher rates than all other students. Second, sociodemographic factors (i.e., annual household income, Pell Grant eligibility, first-generation student status, and age) emerged as key differentiators of predicted conversion rates in three of the four branches (A, B, and C). Third, modality (i.e., online vs. residential) played an important role in differentiating predicted rates of conversion in three of the four branches (A, B, and D). Lastly, factors related to a student's external environment (i.e., relationship status and parenting status) emerged as critical differentiators of conversion in three branches of the tree (B, C, and D) and notably did not play a role in predicting conversion among Black and African American students.

Table 4 Predictors of student conversion by branch and tree level

	Branch A: Black and African American (N=2627)	Branch B: Native Hawaiian/Pacific Islander–Unreported–U.S. Nonresident (N=7146)	Branch C: White–Hispanic/Latino – Asian (N=21,237)	Branch D: American Indian/ Alaska Native–Multiracial (N=842)
Level 2	Pell grant	Relationship status	Relationship status	Relationship status
Level 3	Modality (x2) Household income	Age Household income	Parenting status (x3)	Modality
Level 4	Household income	Pell grant First-generation (x2) Household income Parenting status Race/ethnicity	Age (x3) Transfer hours GPA Household income Modality Pell grant	
Level 5		GPA Age First-generation	Transfer hours (x2) Household income Modality (x2) Pell grant (x2) Gender	
Level 6		GPA	Gender (x3) Race/ethnicity (x2) Household income First-generation Modality (x2)	

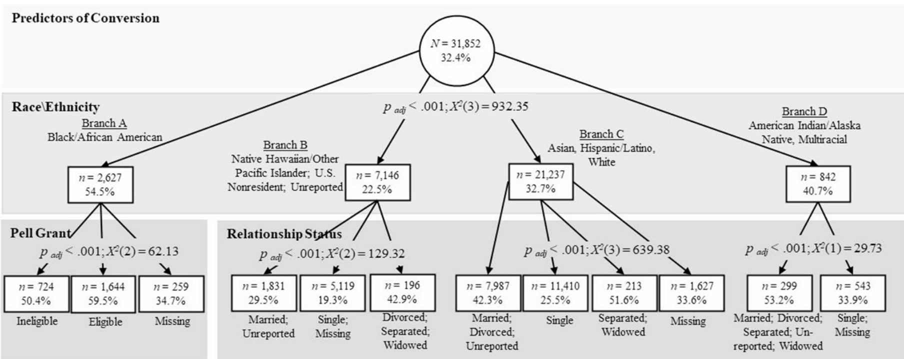


Fig. 2 Student conversion rates in levels 1 and 2 of the classification tree

Conversion among Black and African American Students is Distinctive

The conversion choices of Black and African American students stand out in two ways. First, the CTA model predicted higher rates of conversion for these students as compared to students of other racial and ethnic identities. Second, the factors that predicted conversion among Black and African American students differed from the predictors that appeared in other branches of the classification tree.

Black and African American students, who formed branch A of the classification tree (see Table 4; Fig. 2), were the most likely of all students to enroll in a new program at the university, with a predicted conversion rate of 54.5%. The remaining branches of the tree each contained combinations of students with different racial and ethnic identities. American Indian/Alaska Native and multiracial students (branch D) had the second-highest predicted conversion rate, at 40.7%. Among Asian, Hispanic/Latino, and White students (branch C), the predicted conversion rate was 32.7%. The branch with the lowest predicted conversion rate, 22.5%, comprised Native Hawaiian/Other Pacific Islander students, U.S. Nonresident students, and students who did not report their racial or ethnic identities (branch B).

Not only did the CTA model predict higher rates of conversion among Black and African American students compared to other students, but it also identified a distinct set of factors as contributing to those predictions. Modality and income-specific sociodemographic factors (i.e., annual household income and Pell Grant eligibility) explained conversion rate differences among the students in branch A, whereas modality, a wider array of sociodemographic factors, *and* external environment factors explained differences in predicted conversion rates among the students in branches B, C, and D (see Table 4; Figs. 3, 4 and 5a and b, and 6).

Sociodemographic Factors Predict Student Conversion

Annual household income and Pell Grant eligibility emerged as important predictors of conversion in branches A, B, and C of the classification tree. In all three branches, lower household income and Pell Grant eligibility were almost uniformly associated with higher predicted student conversion rates (see Figs. 3, 4 and 5a, and 5b). Specifically, annual household income explained differences in predicted conversion rates at seven locations in the three branches. In six of those locations, lower income corresponded to higher conversion rates. However, in branch C, married, divorced, or unreported students without children who graduated before age 21 and reported a low annual household income ($\leq$ \$19,508) were predicted to convert to another program less often than their higher-income peers

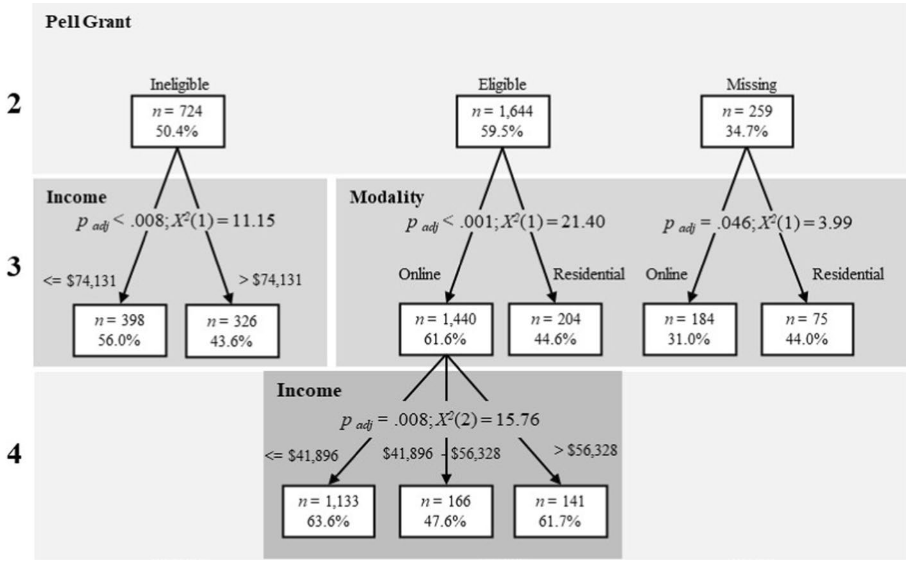


Fig. 3 Branch A: conversion among black and African American students

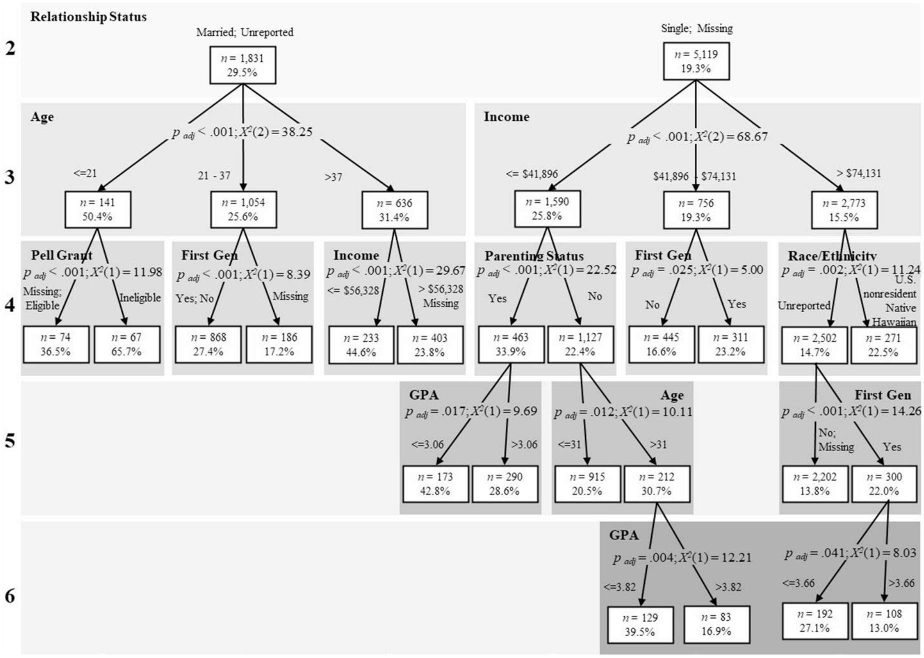


Fig. 4 Branch B: Conversion among native Hawaiian/Pacific Islander, U.S. nonresident, and unreported students

(see Fig. 5a, Level 5). Additionally, Pell Grant eligibility, which is primarily determined by financial need, explained differences in predicted conversion rates in five locations across the three branches. At four of those locations, Pell Grant eligibility corresponded to higher rates of predicted conversion. However, in branch B, Pell eligible students who graduated before age 21 and were married or did not report their relationship status were predicted to convert less often than their Pell ineligible peers (see Fig. 4, Level 4).

Two other sociodemographic factors, first-generation status and age, also played important roles in predicting student conversion. A student's first-generation status explained differences in predicted conversion rates in three locations across branches B and C. In these locations, first-generation students were consistently associated with higher rates of predicted conversion (see Fig. 4, Levels 4 and 5 and Fig. 5a, Level 6). Student age explained differences in predicted conversion rates in five locations across branches B and C. The relationship between age and conversion in these locations was generally curvilinear, meaning that younger students and older students were often predicted to convert at higher rates than students in the middle category; however, the pattern was somewhat inconsistent. For example, among branch C students who were married, divorced, or unreported and who did not have children, age was inversely related to conversion, such that students over age 24 were predicted to convert less often than younger students (see Fig. 5a, Level 4). In contrast, among branch B students from lower income households without children, age was positively related to conversion, with students over age 31 predicted to convert at higher rates than younger students (Fig. 4, Level 5). Thus, while age is predictive, its relationship with conversion may also involve interaction with other factors.

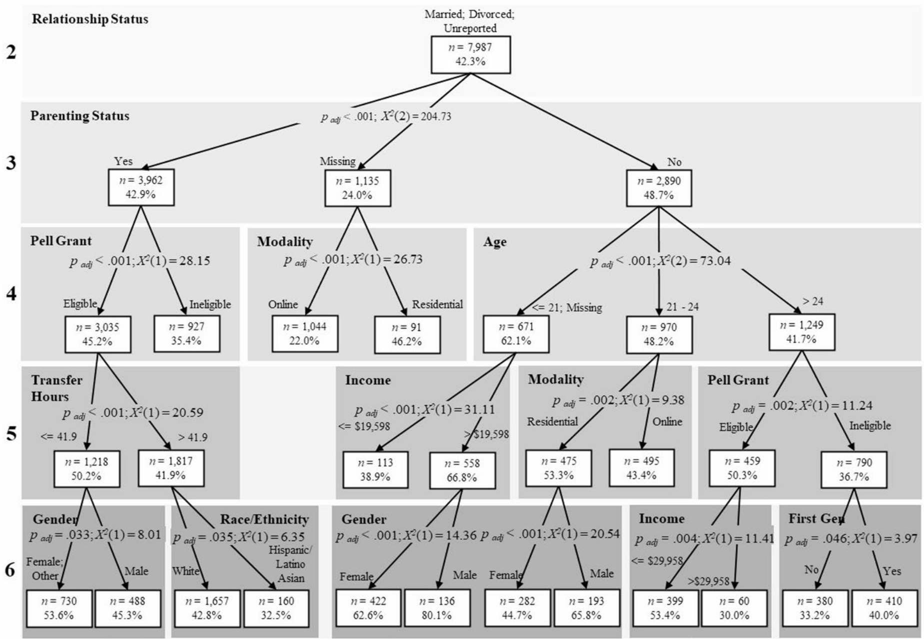


Fig. 5 **a** Branch C, part 1: conversion among Asian, Hispanic/Latino, and white students who were married, divorced, or unreported. **b** Branch C, Part 2: conversion among Asian, Hispanic/Latino, and white students who were single or missing

Modality Predicts Student Conversion

The modality of a student's undergraduate degree program—online or residential—was associated with differences in predicted student conversion rates in eight locations across branches A, C, and D. Among students in branches A and D, who belong to historically minoritized racial and ethnic groups, online undergraduate students were predicted to convert more often than residential undergraduate students in two of three locations in the tree (see Fig. 3, Level 3 and Fig. 4, Level 3). That is, for these students, the on-campus student experience resulted in lower predicted rates of conversion than the online student experience. In contrast, in branch C, residential student status was associated with higher predicted conversion rates in four of five locations (see Fig. 5a, Levels 4 and 5 and Fig. 5b, Levels 5 and 6).

In two locations, Pell Grant eligibility interacted with modality to predict unique student conversion patterns. First, among branch A students whose Pell Grant status was missing, residential undergraduates were predicted to convert at a higher rate than online undergraduates (see Fig. 3, Level 3). This is the opposite trend as compared to students in branch D (see Fig. 6, Level 3) and Pell Grant eligible students in branch A (see Fig. 3, Level 3). Second, among some Pell Grant eligible students in branch C, online students were predicted to convert at a higher rate than residential students (see Fig. 5b, Level 6). This pattern opposes the one that appears in the other four locations in this branch (see Fig. 5a, Levels 4 and 5 and Fig. 5b, Levels 5 and 6).

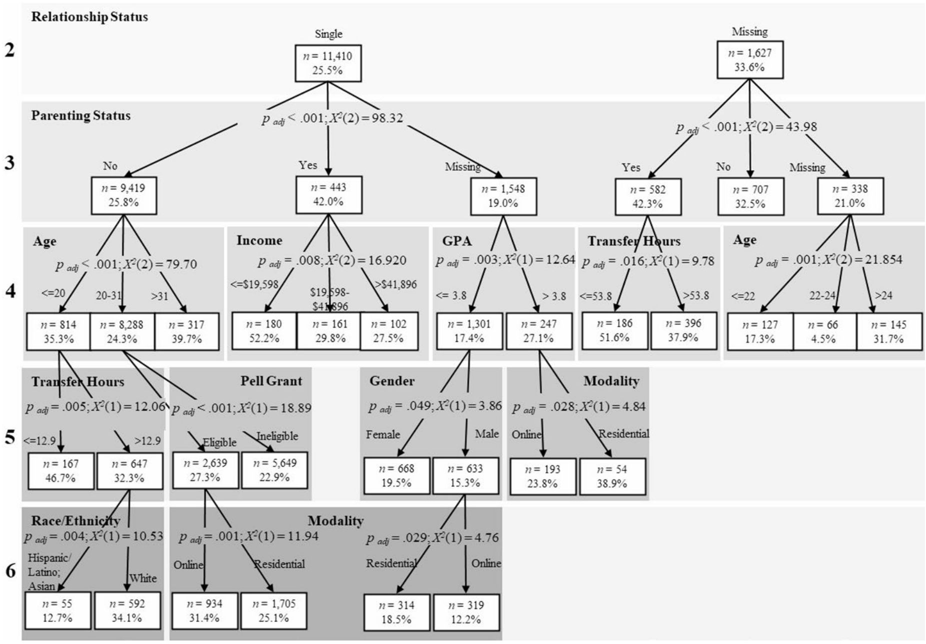
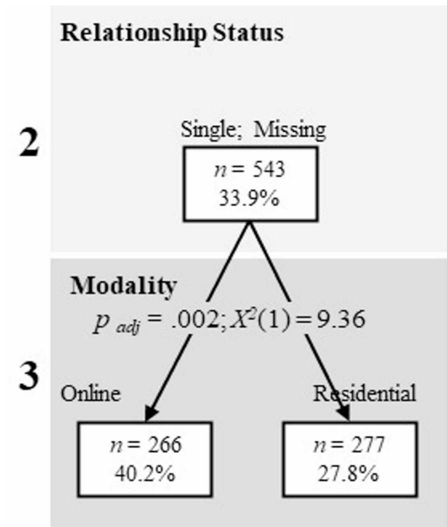


Figure 5 (continued)

Fig. 6 Branch D: conversion among American Indian/Alaska native and multiracial students



External Environment Factors Predict Student Conversion

Two factors representing student's commitments outside the university—relationship status and parenting status—predicted differences in student conversion in various locations in the classification tree. Relationship status played a prominent role, appearing in Level 3 of branches B, C, and D (see Fig. 2, Level 2). Within these branches, single students were predicted to convert at consistently lower rates than students reporting other relationship statuses. Additionally, a student's parenting status predicted differences in conversion in four locations across branches B and C. In three of these locations, students with children were predicted to convert more often (approximately 33–43%) than students without children (approximately 22–33%; see Fig. 4, Level 4, and Fig. 5b, Level 3). Among branch C students who were married, divorced, or whose relationship status was unreported (see Fig. 5a, Level 3), predicted conversion rates were high regardless of parenting status, though students without children were predicted to convert at higher rates (48.7%) than their peers with children (42.9%). Notably, neither relationship status nor parenting status explained differences in predicted student conversion in branch A, further illustrating the distinct routes to conversion for Black and African American students.

Statistical Validity and Algorithmic Fairness

Overall, the CTA model accurately predicted 70% of cases in the full sample (see Table 5). The model was highly accurate in predicting which students did not convert (91.4% specificity, 8.6% false positive rate), but substantially less accurate in predicting which students chose to begin a new degree program at the same university sometime after their college graduation (25.5% sensitivity, 74.5% false negative rate). The resubstitution error rate of 0.300 (30.0%) and cross-validation error rate of 0.308 (30.8%), both with small standard errors (SE = 0.003), suggest that the model is not overfitted to the data.

To explore the statistical fairness of the CTA model across the racial and ethnic identities represented in the study, we applied the model to each of the four branches in the classification tree of the full sample, producing a separate tree for each branch (see Table 4; Fig. 2 for descriptions of the branches). We then ran statistical validity analyses on each of the four branch-specific trees (see Table 6). While previous research on algorithmic bias explores racial and ethnic categories separately or aggregates them based on the categories of privileged and unprivileged (Gándara et al., 2024), this study's CTA model predicted no significant differences in the rate of conversion among the students within each of the four branches, even though branches B, C, and D include students with various racial and

Table 5 Classification tree performance metrics–full sample

Observed	Predicted			Risk		
	No	Yes	Accuracy	Resubstitution	Cross-validation	SE[a]
No	19,661	1859	91.4%			
Yes	7694	2638	25.5%			
Overall	85.9%	14.1%	70.0%	0.300	0.308	0.003
False positive			8.6%			
False negative			74.5%			

[a] The standard error (SE) was consistent across the resubstitution risk estimate and the cross-validation score

Table 6 Classification tree performance metrics by branch

	Predicted		Risk			
Observed	No	Yes	Accuracy	Resubstitution	Cross-Validation	SE[a]
Branch A: Black or African American (n = 2627)						
No	485	709	40.6%			
Yes	348	1085	75.7%			
Overall	31.7%	68.3%	59.8%	0.402	0.423	0.010
False positive			59.4%			
False negative			24.3%			
Branch B: Native Hawaiian/Other Pacific Islander; U.S. Nonresident; Unreported (n = 7146)						
No	5461	74	98.7%			
Yes	1515	96	6.0%			
Overall	97.6%	2.4%	77.8%	0.222	0.224	0.005
False positive			1.3%			
False negative			94.0%			
Branch C: Asian, Hispanic/Latino, White (n = 21,237)						
No	13,472	820	94.3%			
Yes	5768	1177	16.9%			
Overall	90.6%	9.4%	69.0%	0.310	0.319	0.003
False positive			5.7%			
False negative			83.1%			
Branch D: American Indian/Alaska Native; Multiracial (n = 842)						
No	466	33	93.4%			
Yes	279	64	18.7%			
Overall	88.5%	11.5%	62.9%	0.371	0.416	0.017
False positive			6.6%			
False negative			81.3%			

[a] The standard error (SE) value for each classification tree was consistent across the resubstitution risk estimate and the cross-validation score for that tree

ethnic identities. Consequently, we limited our exploration of statistical fairness to these four branches.

The performance metrics for the classification trees produced for the full sample and each branch (see Tables 5 and 6) demonstrate the CTA model's inconsistent statistical validity across students' racial and ethnic identities. The model's overall predictive accuracy for the full sample (70.0%, see Table 4) was similar to its overall accuracy for branch C, higher than branches A and D, and lower than branch B. The similarities between the model's predicted conversion rates (see Fig. 2) and performance metrics (see Tables 5 and 6) for the full sample and branch C likely reflect the fact that branch C represents two thirds (67%; $n = 21{,}237$) of the students in the full sample ($n = 31{,}852$), making it the algorithmic default.

While the CTA model underpredicted conversion for the full sample and branches B, C, and D (all with over 93% specificity and 74% false negative rates; see Tables 4 and 6), it overpredicted conversion among students in branch A (75.7% sensitivity, but only 40.6% specificity and a 59.4% false positive rate). The model's bias toward underpredicting conversion was greatest for the students in branch B, which may explain why this group had the lowest predicted conversion rates (22.5%, see Fig. 2). The model's bias toward overpredicting conversion among the students in branch A is consistent with Gándara et al.'s (2024) observation that machine learning biases can derive from differences in the frequencies of a particular outcome and may explain why this branch's conversion rate (54.5%, see Fig. 2) was substantially higher than that of the other branches. However, the model's high sensitivity when applied to branch A is complicated by its relatively large standard errors and the sample's relatively small size (8.3% of the full sample).

The model was least reliable in predicting conversion among the students in branch D, with low sensitivity and high standard errors. The large gap between the resubstitution and cross-validation error rates in the model when applied to branch D indicate that the model is overfit to the students in this branch, likely due to the group's small sample size (2.6% of the full sample).

Discussion

This study demonstrates how chi-square and classification tree analyses can provide useful insights into the phenomenon of student conversion from undergraduate completion to a new degree program. Our chi-square analysis identified a relationship between academic discipline and student conversion at a single university over an 11-year period, such that undergraduates earning degrees in the humanities and social sciences were more likely to enroll in new programs at the same university than their peers earning bachelor's degrees in the natural and applied sciences. In our CTA model, sociodemographic factors, modality, and external environment factors all contributed to predicting which students crossed the bridge from college graduation to subsequent degree programs. Our findings have implications for tuition-driven universities, particularly those seeking to reduce enrollment management costs by retaining more of their undergraduates in new degree programs. While this study focuses on data from a single institution, it uses longitudinal student records common to all institutions and offers a theoretical and methodological framework for institutions to study conversion patterns among their own students.

The relationship between academic discipline and student conversion may reflect both the characteristics of a single university and broader trends across higher education. For instance, the university in this study may have notable strengths in the humanities and social sciences, resulting in a wide array of available programs or a strong academic reputation in these disciplines that may compel graduates to return to pursue an additional degree. It may also be the case that the university offers fewer online programs in the natural and applied sciences, reflecting a more universal need for degree programs in these disciplines to require on-campus learning experiences such as laboratory work and resulting in less frequent conversion among online students living far away from the university. Because the interaction between the characteristics of an individual university and regional or national higher education norms will be unique for each institution, the nuances of the relationship between academic discipline and student conversion may differ from school to school.

In the CTA model generated from our data, Black and African American students were predicted to convert more frequently than students of other racial and ethnic identities (see Fig. 2). While the model overpredicted conversion among this group of students, the categorization of these students within their own branch of the classification tree illustrates the distinctiveness of their enrollment patterns. The higher predicted rate of conversion among these students aligns with numerous prior studies in which Black and African American students were more likely than students of other racial and ethnic identities to aspire to, apply to, and attend graduate school (English & Umbach, 2016; Mattern & Radunzel, 2015; Perna, 2004; Wolniak et al., 2020). In accordance with recent research (McCoy & Winkle-Wagner, 2022; McGee et al., 2016; Washington et al., 2024), it is possible that the Black and African American students in this study were particularly driven to pursue additional degrees by a desire to give back to the cultures, communities, and families in which they grew up. Furthermore, these motivated students may perceive specific advantages to advancing their education at their alma mater, such as established familiarity with the institution and positive relationships with faculty.

Another distinctive pattern among the Black and African American students in this study is the prominent role of income-specific sociodemographic factors (i.e., annual household income and Pell Grant eligibility) and modality in predicting these students' likelihood of pursuing an additional degree at the same university (see Table 3; Fig. 3). This finding suggests that these students may prioritize potential benefits such as convenience and financial savings when deciding whether to convert. For example, it may be the case that converting to a new degree at the university offered a cost savings that some students found appealing, particularly if their target program was a well-regarded one. Additionally, some online undergraduates may have elected to convert because the university offered a degree in their desired field, allowing them to continue their education without relocating or changing jobs.

In the three branches of the classification tree where socioeconomic status explained differences in predicted student conversion rates, lower annual household income and Pell Grant eligibility were almost uniformly associated with higher predicted rates of student conversion (see Figs. 3, 4 and 5a, and 5b). However, in two locations in the classification tree, the opposite relationship appeared (see Fig. 4, Level 4 and Fig. 5a, Level 5). These mixed findings reflect a disagreement in the broader research literature regarding the relationship between socioeconomic status and graduate school advancement (English & Umbach, 2016; Ethington & Smart, 1986; Mattern & Radunzel, 2015; Wolniak et al., 2020; Xu, 2016; Zhang, 2005). Overall, our results indicate that students from lower-income households in this study saw financial advantages to remaining at their undergraduate institution for another degree, allowing them to more easily expand their career opportunities or achieve upward mobility through continued education.

The CTA model predicted that first-generation students were more likely than continuing-generation students to convert to a new degree program (see Figs. 4 and 5a), which differs from the findings of numerous prior studies indicating that students with highly educated parents are more likely to aspire to, apply to, and attend graduate school (English & Umbridge, 2016; Ethington & Smart, 1986; Mullen et al., 2003; Nevill & Chen, 2007; Pascarella, 1984; Perna, 2004; Posselt & Grodsky, 2017; Xu, 2016; Zhang, 2005). It may be the case that the first-generation students in this study faced unique challenges in changing universities for another degree, including perceived differences in social and cultural capital and actual differences in financial resources, as compared to their continuing-generation peers (Bahack & Addi-Raccah, 2022). As a result, these students may have felt more confident about beginning a new enrollment at the same university.

The classification tree also predicted higher conversion rates for younger and older students than their peers (see Figs. 4 and 5a, and 5b). The relationship we observed between student age and conversion aligns with earlier research indicating that younger and older students enroll in graduate school more often than students near the age of 30 (Nevill & Chen, 2007; Xu, 2014; Zhang, 2005). The alignment between our results and prior research suggests that lower rates of conversion among students near age 30 may reflect broader trends in graduate school advancement. Adults in their late 20s and early 30s may be in a busier stage of life—one often marked by marriage, the birth of children, and career advancement—that pulls their focus away from educational attainment.

Our analysis also revealed that modality interacted with racial and ethnic identity and, in some cases, Pell Grant eligibility to explain differences in predicted rates of student conversion (see Figs. 3 and 5a and b, and 6). In two branches of the tree that represented students with marginalized racial and ethnic identities, the CTA model predicted that online undergraduates were more likely than residential undergraduates to remain at their university to pursue another degree (see Figs. 3 and 6). However, in the branch representing students with a mix of dominant and marginalized racial and ethnic identities, the opposite was true; residential students were more likely than online students to convert to a new program (see Fig. 5a and b). Additionally, Black and African American students with missing Pell Grant eligibility information (which likely indicates they were Pell ineligible) were predicted to be more likely to convert if they were residential students (see Fig. 3), whereas Pell eligible students from a combination of marginalized and dominant racial and ethnic groups were more likely to convert if they completed their undergraduate degrees online (see Fig. 5b).

The interaction between modality, racial and ethnic identity, and Pell Grant eligibility can be interpreted in two ways. It is possible that a poor sense of belonging among socioeconomically or racially and ethnically marginalized students on the university's residential campus (Gopalan & Brady, 2020; Soria et al., 2013) may have reduced these students' motivation to pursue another degree at the same institution (Tinto, 2025). However, online students, who typically complete their coursework away from a physical campus, may be less likely to feel alienated by an exclusionary on-campus climate. As a result, these students may feel more inclined to remain at their undergraduate university for a new degree. Alternatively, the results may suggest that online degree programs expand educational opportunities for marginalized students (Goodman et al., 2019), who more frequently experience barriers to full-time, on-campus study (Beckwith, 2023; Means, 2025; Thiem & Dasgupta, 2022). For example, online education can offer essential flexibility to students with heavy work demands or caregiving responsibilities, who may not be able to commit to courses that occur in fixed physical locations at specified times.

Finally, single (unmarried) students in this study were predicted to convert to new degree programs less often than their peers, and in most cases where parenting status was a predictive factor, student-parents converted more often than students without children (see Figs. 4 and 5a and b, and 6). These findings deviate from prior research indicating that single students and students without children are more likely to enroll in or complete a graduate program than students in relationships and student-parents, respectively (Nevill & Chen, 2007; Xu, 2014, 2016). In this analysis, single students may be moving to other universities for additional degrees. It may be easier for them to relocate than married, separated, divorced, or widowed students, who may have deeper familial connections to a specific geographic location. Likewise, because they may be less inclined to disrupt their children's lives with a relocation, student-parents may be more inclined to pursue another degree at their undergraduate university.

It is important to consider the accuracy and fairness of a machine learning model in predicting outcomes for diverse student groups (Anglin, 2024; Baker et al., 2023; Gándara et al., 2024). Our analyses of statistical validity and algorithmic fairness indicated that while our CTA model performed moderately well (70% overall accuracy; see Table 5), it underpredicted student conversion across the full dataset. Furthermore, the validity of the model's predictions differed based on students' racial and ethnic identities (see Table 6). The model overpredicted conversion among Black and African American students while underpredicting conversion among all other students. While this study illustrates that CTA models can be used to help university stakeholders better understand patterns in student conversion at their institutions, our model's performance demonstrates that it is critical to interpret machine learning predictions carefully and with an eye toward the potential influence of social biases.

Limitations and Recommendations for Future Research

Although we gave thoughtful attention to the retrieval of records, data queries, and data analysis, we also recognize some limitations to this study. First, the data represent student conversion at only one institution, though the diversity and size of the institution comprise a robust higher education ecosystem. Second, the data do not account for additional factors that may impact student conversion, such as enrollment status (full or part-time) and the amount of institutional financial aid individual students received. Third, it was beyond the scope of this study to identify separate sets of factors that predict student conversion within each of the academic disciplines. Future research is needed to disentangle unique predictors of conversion across disciplines, where the modality and degree level of subsequent programs can be incorporated to develop a more nuanced model of conversion patterns. Fourth, the CTA does not provide insight into factors (e.g., course availability or changes in university practices or policies) that may contribute to differences in undergraduate degree completion rates or the length of time to conversion among different student groups. Therefore, it will be essential to incorporate these factors into future research. Finally, it is important to note that the cohorts included in this study span the COVID-19 pandemic. While past research has merged data from pre- and post-pandemic cohorts for analysis (Matz et al., 2023; Simeunovic et al., 2024), it is possible that the pandemic may have influenced trajectories of conversion. These five limitations pose opportunities for future work in this important area.

We also suggest that future studies examining student conversion should advance beyond this initial inquiry to include additional student groups such as athletes, disabled students, participants in student clubs and organizations, and those employed on campus. Understanding these students' patterns of successful or unsuccessful conversion will impact not only student recruitment, but also programmatic improvement that maximizes the efficacy of financial investments in essential student services. Additionally, we suggest that future studies include multiple campuses to improve the generalizability of results. This type of approach will add breadth to the depth this study emphasizes.

Implications

From an institutional perspective, students who convert from undergraduate completion to new degree programs at the same institution represent a type of cost savings: Undergraduate students who are already part of the university community do not have to be recruited into new programs in the same costly manner as undergraduate students attending other institutions, thus spreading the cost associated with acquiring a student across more than the traditional four years of undergraduate study. Following from this premise, our findings have implications for practice for colleges and universities striving to contain costs and improve student success.

First, this study provides administrators and institutional researchers with a new measure of student success and an analytical technique (CTA) by which they can “map” patterns of student conversion in their respective institutions and contexts. This predictive analytical approach enables administrators to identify patterns of conversion that can inform institutional decision-making, ultimately improving student retention both within and across degree and certificate programs. The granular nature of the data helps identify different student profiles who can then be proactively targeted to receive institutional support measures during an important period of educational transition. Furthermore, focusing on developing a better understanding of the bridge between degree or certificate programs is an important area of highlighting new and emergent opportunities for enrolling graduates in additional degree programs.

Second, the results of the CTA provide university leaders with two actionable areas of focus: student recruitment and program development. In the area of student recruitment, it is beneficial for administrators to know which student groups are less likely to convert from undergraduate completion to another degree, as these groups may require additional recruitment efforts and costs. Results from CTA can also provide university leaders with information to improve academic program development. For example, the characteristics of students who do not convert may signal a misalignment between their interests and current program offerings, thereby creating an opportunity for a university to explore new program structures, short-term credentials, or other modalities that better serve those populations. By using CTA results to focus on both student recruitment costs and targeted program development, university leaders can optimize the financial health of their institutions.

Lastly, the exploratory nature of this study required that we assess field-based data illustrating real limitations encountered daily by colleges and universities. For example, some might view the missing/not reported categories of data in this study as a methodological shortcoming. However, we contend these categories represent areas of action and inquiry for institutions when discovered. For instance, when we reviewed the missing/not reported categories of data over time, we discovered changes in two important areas: racial and ethnic identity and relationship status. The percentage of unreported data for racial and ethnic identity increases from 14.6% in 2013, peaks at 25.9% in 2018, and remains at 22% in 2020. Similarly, the percentage of missing data for relationship status increases from 4.1% in 2013 to 25% in 2020. The changes in these two important categories highlight a possible area of mistrust between the institution and its students, with students essentially saying, “I will not give you this information about me.” On the other hand, missing and unreported data might reflect a lack of institutional coordination across data systems, therefore limiting institutional knowledge and decision-making that could further optimize the financial health of the institution.

Conclusion

Focusing on student conversion—the transition between the end of one enrollment and the initiation of a subsequent enrollment *at the same institution*—offers a new retention perspective leaders can employ to improve student academic success and reduce enrollment costs. In our study, we highlight that one-third of all students who completed an undergraduate degree at one large U.S. university successfully converted to a new program of study at the same institution. Furthermore, in our analysis of both on-campus and online students, we found that distinct sets of factors predicted conversion within different student groups. This study offers practical implications for higher education leaders seeking to improve student success or identify points of student conversion to strengthen student enrollment or program development.

This examination of student conversion is the first assessment we have taken to further understand a single decision point among the myriad decision points a student makes in the progression of their life course journey from college admission to labor market entry. Further application of the student conversion measurement and framework will help scholars and university leaders understand the academic journey at each decision point, thus deepening the college-student relationship as well as strengthening student enrollment and academic success.

Conflict of interest The authors did not receive support from any organization for the submitted work. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no conflict of interest to declare that are relevant to the content of this article.

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