Survival Analysis of Transfer Students

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Abstract

Research conducted on transfer student outcomes consistently shows that there is a bachelor's degree completion gap between transfer students and nontransfer students. Researchers have explored several factors thought to impact bachelor's degree completion for transfer students, including demographic characteristics, number of credit hours transferred, transfer GPA, transfer institution type, and indicators of academic achievement. The findings from these studies have not always been consistent in whether (or how) these factors influence degree completion. The current study uses survival analysis to better understand college persistence for students transferring to a large, 4-year, public university located in the Southeast United States. Survival analysis, a statistical technique underutilized in higher education research, has several advantages over more traditional methods, such as regression. For example, survival analysis not only has the capacity to examine time-varying predictors, but also can include both uncensored and censored events (i.e., it can handle both students for whom the event of interest occurs during the time frame under investigation and students for whom it does not). In addition to variables explored in previous research, this study investigated aspects of students' majors (i.e., whether they changed majors after enrollment and whether majors were in STEM fields). Findings indicate that transfer students who are most likely to persist are generally younger, are full-time students, and are in STEM majors; and that they have higher prior academic achievement, a greater numbers of transfer hours, and at least one major change.

Keywords: survival analysis, transfer students, college students, persistence

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INTRODUCTION

Today's students often transition between different types of higher education institutions and pursue nontraditional pathways in their quest to complete a postsecondary degree. Not uncommonly, students enroll in 4-year universities after having attained an associate's degree, or, at least, some credit hours at a community college. This trend underscores the importance of examining the outcomes of transfer students, who face unique challenges and opportunities in their quest for bachelor's degrees. Despite the increasing prevalence of such nontraditional education pathways, research conducted on transfer student outcomes consistently shows that there is a bachelor's degree completion gap between transfer students and nontransfer students. For example, Shapiro et al. (2017) tracked a cohort of community college students for 6 years, beginning in 2010. Of the students who transferred to bachelor's degree–granting institutions, 42% attained bachelor's degrees. The American Council on Education's (2021) National Task Force on the Transfer and Award of Credit, citing the Shapiro et al. study, pointed out that "this rate of baccalaureate completion represents a roughly 17 percent gap for transfer students compared to students who receive a degree within the same institution of attendance (without transfer)" (p. 35). This discrepancy points to a critical need for higher education institutions to better understand and support the unique needs of transfer students.

The significance of studying transfer students extends beyond academic achievement to encompass broader implications for both students and institutions. From a student's perspective, successful completion of a bachelor's degree can significantly impact lifetime earnings, employment opportunities, and social mobility (Baum et al., 2013). For institutions, improving transfer student outcomes not only is a matter of academic responsibility, but also has financial implications, affecting enrollment management, resource allocation, and institutional reputation (Tinto, 1993). Furthermore, as higher education faces increasing scrutiny over costs and value, demonstrating success in facilitating transfer students' completion becomes paramount for institutional accountability and sustainability.

The current study seeks to contribute to the literature on college persistence by using survival analysis, a statistical technique that, despite its potential, has been underutilized in higher education research. Survival analysis offers a nuanced approach to examining the time-dependent nature of student retention and completion, allowing for the inclusion of both censored and uncensored values (i.e., data for students for whom the event of interest occurs during the time frame under investigation and students for whom it does not) and the assessment of time-varying predictors (Ronco, 1995). This methodological choice is particularly relevant for studying transfer students, whose educational pathways may be more varied and complex than those of first-time-in-college students.

Unique to this study is the inclusion of two variables related to student major, addressing a gap in the existing literature. Previous research has often overlooked the role of academic discipline in influencing student outcomes, despite evidence suggesting that major choice can significantly impact persistence rates (Wright, 2018). By incorporating these variables, the study offers new insights into the factors that contribute to transfer students' success. The context of the institution in the study—a large, 4-year, public university—is especially pertinent, given the growing recognition of the role of public universities in providing accessible and affordable education to a diverse student body, including transfer students. This focus becomes even more significant because this university is increasingly attempting to understand and support the unique pathways to graduation for transfer students, moving beyond the traditional emphasis on first-time-in-college students.

LITERATURE REVIEW

Before describing the statistical analysis and results, a review of the literature will be presented, detailing key factors that have been found to impact student persistence. The literature is reviewed in two sections: The first section includes studies using analytic techniques other than survival analysis; the second section focuses specifically on studies that did use survival analysis. Note that, due to the low number of studies utilizing survival analysis to investigate transfer student success in college, some studies have been included in the latter section that focus on first-time-in-college students.

Non–Survival Analysis Studies

As noted by Barbera et al. (2017), research spanning several decades has attempted to understand predictors of student success in undergraduate degree programs. Studies have demonstrated that demographic variables, community college credentials, the number of credit hours transferred, and transfer institution type are all factors that influence transfer students' persistence rates.

DEMOGRAPHIC VARIABLES

The impact of student demographics on transfer student persistence rates is underscored in recent research by Marbouti et al. (2021) that focuses on students within San Jose State University's College of Engineering, a large percentage of whom were transfer students. Their study highlights significant disparities among students, particularly concerning ethnicity, gender, and financial aid patterns. Despite eligibility for financial assistance, Hispanic, first-generation, and low-income transfer students exhibit lower GPAs and experience delays in graduation. Wang (2009), utilizing data from the National Education Longitudinal Study of 1988 and the Postsecondary Transcript Study, examined graduation probabilities for community college transfers to 4-year institutions and revealed a gender discrepancy, with females demonstrating a higher likelihood of completing bachelor's degrees, even after accounting for other variables. Taplin's (2019) research at a large public university identified a significant association between family income (indicated by Pell grant eligibility) and both 1-year retention and 6-year graduation rates among transfer students.

COMMUNITY COLLEGE CREDENTIALS

The impact of earning an associate's degree on whether students go on to complete a bachelor's degree yields mixed findings (Zhang, 2022). On the one hand, some research suggests a positive influence of obtaining an associate's degree on community college students' likelihood of transferring to a 4-year university and achieving academic success post-transfer (Daddona et al., 2021). For example, Kopko and Crosta (2016) conducted logistic regression analysis on a statewide sample and discovered that transfer students entering a 4-year institution with an Associate of Arts or Associate of Science degree were approximately 50% more likely to graduate within 6 years compared to transfer students without an associate's degree. However, possession of an Associate of Applied Science degree did not enhance the likelihood of bachelor's degree attainment within 6 years.

Other research suggests that acquiring an associate's degree prior to transfer may not significantly affect students' academic success at 4-year institutions (Wang, Chuang, et al., 2017). Jenkins and Fink (2016), leveraging data from the National Student Clearinghouse, concluded that the relationship between community college credentials and bachelor's degree completion within 6 years was not universally observed across many states. Some authors suggest that the number of credits accepted by the receiving 4-year institution is more predictive of a transfer student's academic outcome than simply possessing an associate's degree (Monaghan & Attewell, 2015; Zhang, 2022).

NUMBER OF CREDIT HOURS TRANSFERRED

The existing literature presents a diverse range of findings regarding the relationship between transfer student success and the volume of transferred credit hours. Some studies suggest that transferring a greater number of credit hours correlates positively with transfer student success (Yang et al., 2018). These studies indicate that students who transfer more credits are more likely to fulfill degree requirements promptly and to achieve better academic performance (Daddona et al., 2021).

Conversely, other research offers nuanced perspectives, suggesting that, while transferring a substantial number of credit hours may seem advantageous initially, it can also pose challenges. For example, students transferring many credits may face difficulties assimilating into the new academic environment, meeting remaining degree requirements, or accessing necessary support services (Gardner et al., 2021).

If a relationship exists between number of transferred credit hours and transfer student success in college, it may not be a simple one. Luo et al. (2007) used an institutional sample of 1,713 transfer students from five cohorts, categorized by entering class level (freshman, sophomore, junior), as determined by credit hours transferred. Through sequential logistic regression, they found that different factors influenced retention for the three class levels. For entering freshmen, retention was predicted by gender and first-term GPA. Retention to the 2nd year for entering sophomores was predicted by hours transferred, but there were interactions with financial aid, age, and 1st-year GPA. One-year retention for entering juniors was predicted by a set of interacting factors: transfer credit hours, total credit hours, and GPA earned post-transfer.

TRANSFER INSTITUTION TYPE

Aulck and West (2017) performed a descriptive analysis of transcripts from nearly 70,000 entering students over an 8-year period at a large public institution to investigate persistence and attrition. They compared native freshmen, transfers from 2-year institutions, and transfers from 4-year institutions, and found that native freshmen and 2-year transfers had similar attrition rates and GPAs. Transfers from 4-year schools had higher GPAs than the other two groups but also had higher rates of attrition.

Survival Analysis Studies

Although not as common as statistical techniques such as regression analysis, some research studies in higher education have utilized survival analysis to examine factors that impact student persistence rates in the areas of student demographics, academic achievement, and college experience.

STUDENT DEMOGRAPHICS

Demeter et al. (2022) examined the role of student demographics in predicting time to degree completion. They found that factors such as gender, race/ethnicity, and first-generation status were significant predictors of graduation probability. Consistently, studies have confirmed the influence of gender on college persistence. For instance, Ronco (1995) reported that gender played a role, albeit a small one, in predicting exit, with female students slightly more likely to graduate than male students. Similarly, Wang, Wang, et al. (2017) revealed that female students tend to have a higher probability of degree completion. Hayward (2011) reported that gender (male) had a small negative effect on transfer. Chimka et al. (2007) found gender differences related to standardized test scores. Female students with better standardized math scores were more likely than similar male students to graduate. As far as race/ethnicity is concerned, Lin et al. (2020) noticed that a significant gap in the likelihood of bachelor's degree completion between Black and White students emerged more episodically, while the gap between Hispanic and White students developed earlier and remained more consistent over time. Wang, Wang, et al. (2017) also noted that the probability of completing a degree is higher for White students. In addition, in Murtaugh et al. (1999), univariate analysis suggested that Black, Hispanic, and American Indian students are at greater risk of withdrawing than are White students; the differences disappeared in a multivariate analysis, however, and Black students seemed to have reduced withdrawal risk, compared to White students. Lin et al. (2020) discovered that achieving academic milestones, such as credit momentum and the completion of pre-transfer associate's degrees, benefits all students, but benefits Black and Hispanic students disproportionately.

Fewer studies are available examining the relationship between socioeconomic status (SES) and college persistence. A notable exception is a study by Reynolds and Cruise (2020) who focused on the impact of SES on student retention. They found that students from lower-income backgrounds had a higher hazard rate of dropping out compared to their higher-income counterparts. Hutton (2015) suggested that financial aid had a small negative impact on graduation with, not surprisingly, the odds of departure lower when higher percentages of educational cost were covered by financial aid.

Not all researchers have found demographic variables to influence college persistence. Hutton (2015), for example, used discrete-time survival analysis to examine factors predicting community college students' completions at a public university, and concluded that college persistence and completion appeared to be unaffected by demographic variables. Finally, regarding age, results are mixed. As students age, according to research by Hayward (2011), they are generally less likely to transfer. If older students do transfer, however, according to Murtaugh et al. (1999), they are less likely to be retained. On the other hand, Wang, Wang, et al. (2017) found that older students tend to have a higher probability of degree completion.

ACADEMIC ACHIEVEMENT

Survival analysis has also been utilized in higher education research to examine the impact of academic achievement on student persistence rates. In general, researchers have found that persistence increases with better high school GPAs (Choudhury & Runco, 2020; Miller & Lesik, 2014; Murtaugh et al., 1999). For example, a study by Allensworth and Clark (2020) examined the relationship between high school GPA and time to graduation from college. They found that students with higher high school GPAs were less likely to drop out and took less time to graduate from college. However, Voelkle and Sander (2008) pointed out that the effect of high school GPA on dropping out of college may be completely mediated by university GPA, so there would be no additional predictive ability of high school GPA over university GPA. ACT and SAT scores are also important predictors: McNeish et al. (2020) explored the predictive power of standardized test scores on student retention. They found that students with higher test scores were less likely to drop out of college and graduated more quickly than students with lower scores. Looking at several academic achievement variables used in the college admissions process, Miller and Lesik (2014) found that retention was associated with higher entry-level academic preparation (ELAP) scores (categorized into high, medium, and low), and that the effect was consistent across time. ELAP was determined by a combination of ACT score, high school class rank, and the number of college prep units. Students with higher ELAP were found to be more likely to graduate in Years 4 and 5 compared to students with lower ELAP scores.

Achievement at a community college has also been shown to be related to likelihood of graduation with a bachelor's degree after transfer. In the study by Hutton (2015), the number of earned community college credit hours had a small but positive impact on graduation, while the attainment of an associate's degree had a larger positive impact. Hutton also noted that semester GPA had a strong impact on the odds that a student would eventually graduate or depart before graduation. The importance of college GPA as a predictor of outcomes is confirmed in many studies. For example, Murtaugh et al. (1999) found that retention increases with increasing first-quarter GPA. Similarly, Ronco (1995) found that students who exit through dropout or transfer are most likely to do so because of the immediate impact of a GPA below 2.0, with students having failing GPAs six and a half times more likely to drop out and eight and a half times more likely to transfer.

A full-time enrollment status is found to be positively related to graduation or credential completion and negatively related to dropout or transfer (Ronco, 1995; Wang, Wang, et al., 2017). Hutton's (2015) study confirmed that students who stop out (i.e., who leave college but eventually return) and were part-time students had significantly lower graduation rates and higher departure rates.

COLLEGE EXPERIENCE

Within the scope of understanding persistence rates for transfer students, using survival analysis offers a nuanced lens to explore the dynamic interplay between engagement in the college experience and these pivotal academic outcomes. For example, a study by Caruth (2018) explored the relationship between student engagement and time to graduation. Caruth found that students who were more engaged in campus activities and who had higher levels of social integration had a lower hazard rate of drop out or delay to graduation.

In the study by Miller and Lesik (2014), the effect of 1st-year experience participation on retention was found only for the 1st year, but the influence of 1st-year seminar participation reappeared for 4-year graduation, perhaps due to an indirect variable such as beginning college ability. In Choudhury and Runco's (2020) study, results suggested that a university course that focuses on time management, note-taking, test-taking, studying, and so on increases the retention rate by approximately 38%. Murtaugh et al. (1999) also found that students taking a freshman orientation course appeared to be at reduced risk of dropping out.

There is evidence that transfer shock, typically defined as a drop in GPA between pre- and post-transfer institutions, plays a role in student departure. In a study of North Carolina community college transfer students, the odds of departure were higher for students who experienced transfer shock; there was no statistically significant effect on graduation, however (Hutton, 2015).

Based on these findings, one can conclude that it is meaningful to conduct a multivariate survival analysis incorporating variables related to pre-academic preparation, college experience, and demographics. This conclusion can be supported by one of the findings from Miller and Lesik (2014), who noted that differing results were found in a survival analysis than in a descriptive analysis. For example, descriptive analysis showed a positive impact of 1st-year seminar across all ability levels, but survival models showed only initial effects. Murtaugh et al. (1999) also observed that the relationship between retention and race and/or ethnicity was different in the univariate versus multivariate views. Finally, Mourad and Hong (2008) emphasized the importance of considering the interaction effect of time and other variables. In their study, the effect of time resulted in changes from a statistically significant to a nonsignificant relationship, or from a nonsignificant to a statistically significant relationship for some variables. However, very few studies (Hutton, 2015; Lichtenberger & Dietrich, 2017) have used survival analysis to better understand transfer student persistence. To fill this gap, the current study used survival analysis to investigate the persistence of transfer students during their (initial) 4 years at the transfer institution. Specifically, the research addressed the following questions:

1| What is the estimated survival rate of transfer students within eight semesters after enrollment?

2| Are there significant differences between the survival rates of subgroups based on age, major, major change, transfer GPA, number of transfer credit hours, financial aid received, enrollment status, race and/or ethnicity, and/or gender?

3| How large are the effects of covariates on transfer students' persistence rates?

METHODS

Quantitative studies of college retention and completion have most often used regression models. Another statistical technique that has been gaining in popularity within higher education research is survival analysis. Survival analysis refers to "a set of statistical methods for investigating the time it takes for an event of interest to occur" (Statistical Tools for High-throughput Data Analysis [STHDA], n.d.). The origins of survival analysis can be traced back to early work on mortality in the 17th century (Lee & Go, 1997). Depending on the research focus and the academic field, survival analysis can also be referred to as event history analysis, duration analysis, hazard modeling, reliability analysis, or transition analysis (Box-Steffensmeier & Jones, 2004; Ronco, 1995). The meaning of the term "survival" is also context dependent. For example, in the medical field "surviving" means a patient does not experience a death event. In the education field, if the outcome of interest is attrition, "surviving" means a student does not drop out. Survival analysis has several advantages over traditional regression methods. First, the analysis can include both uncensored and censored events (i.e., include both students for whom the event of interest occurs during the timeframe under investigation and students for whom it does not); second, it has the capacity to examine time-varying predictors (e.g., students' term GPA); and third, the analysis can determine the relative importance of predictors on outcomes of interest (Ronco, 1995).

Data Set

In this study, transfer students are defined as students who started work toward a degree program in one postsecondary institution and then transferred to a different postsecondary institution with the intention of completing their degree. The study institution is a large public R2 (high research activity) university located in the Southeast United States. Transfer students account for about one-third of entering undergraduate students each year, with the largest proportion coming from North Carolina community colleges. The study population comprised all new transfer students entering the institution in the Summer or Fall terms of 2010 to 2017. For each student, the data set included indicators of enrollment (enrolled or not enrolled) in each term following entry up to eight semesters. Students who were not enrolled in a term were counted as having dropped out even if they subsequently reenrolled within the years under investigation. Data were retrieved from the university's data warehouse by the university's institutional research staff, with queries written in SQL and SAS. A total of 11,267 students were included in the final analysis, with an average age of 25, average transfer GPA of 3.10, and an average of 57 credit hours transferred. Table 1 presents additional characteristics of these students.

Table 1. Summary of Student Characteristics (N = 11,267)

Characteristic	N	%
Entered with an associate's degree	4,136	37%
Enrolled full time in their first semester	8,341	74%
Entered as declared or intended STEM majors*	2,406	21%
Changed major during 1st year	1,862	17%
Any financial aid received	8,388	74%
Pell grant received	5,117	45%
Need-based aid received	8,211	73%
Merit-based aid received	473	4%
Female	6,134	54%
Underrepresented minority**	2,681	24%

** Note: As identified by the U.S. Department of Homeland Security (DHS), n.d.*
*** Includes American Indian/Alaska Native, Black/African American, Hispanic, Native Hawaiian or Other Pacific Islander, and Two or More Races.*

A total of eleven variables were included in the analysis: nine covariates, one time variable (the number of semesters a student was enrolled), and one outcome variable. The outcome variable was a binary variable that indicated whether students left the university without graduating after the last semester in which they were enrolled. Students who graduated or were still enrolled within the period under investigation were in one category (Persisted, coded as 0) while students who left the university and did not return were in another (Departed, coded as 1). Several of the covariates could be considered time variant (i.e., changed major, STEM major, financial aid received, and enrollment status). All covariates are described in Table 2.

Table 2. Covariate Descriptions

Variable	Definition
AGE_AT_MATRIC	Age at first enrollment
CHANGED_MAJOR	Whether a student changed major in Year 1 (Y, N)
STEM_MAJOR	Major at end of Year 1 is a STEM major (Y, N)
TRANSFER_CREDIT_HOURS	Total hours transferred in
TRANSFER_UG_GPA	Transfer undergraduate GPA
FIN_AID_RECEIVED	Received any financial aid Year 1 (Y, N)
FT_PT_Flag	Full-time or Part-time status in first term (FT, PT)
GENDER	Female / Male
URM*	URM / Non-URM

* Note that race/ethnicity was represented by a dichotomous variable of underrepresented minority (URM) or non-URM. We define URM as race/ethnicity categories that are underrepresented in our student body relative to their representation in the region.

DATA ANALYSIS

Data were analyzed using the statistical software R. More detail on the basics of survival analysis can be found on the webpage for STHDA (n.d.) and in PowerPoint slides made available online as part of a workshop titled "Introduction to Survival Analysis in R" (UCLA Office of Advanced Research Computing, Statistical Methods and Data Analytics, n.d.). For the first research question, the Kaplan-Meier curve was used to estimate and visualize survival probability from Semester 1 to Semester 8. The Kaplin-Meier curve graphically represents the survival function and shows the probability of an event at a given time interval. The x axis represents time—in our case, the number of semesters elapsed since entry. The y-axis presents the estimated survival rate. Kaplin-Meier allows for the inclusion of censored data (i.e., data on cases for which the event has not yet occurred). As mentioned previously, the ability to utilize censored data is one of the major advantages of survival analysis over other statistical techniques such as logistic regression. For student data, regression examines only whether a student had or had not experienced the event of interest (e.g., retention) at a particular point in time. Survival analysis, however, allows for including data on "censored" students (i.e., students for whom we do not know an outcome by the end of a specific time period but about whom we have data from within a given timeframe). For the second question, the Stratified Kaplan-Meier plot was used to estimate and visualize survival curves, and the log-rank test was used to compare whether there was a difference between the survival curves of the seven selected groups. Finally, the Cox proportional hazard model was used to examine the relationships between the covariates and transfer students' persistence. The log-rank test also helps in variable selection in the Cox proportional hazard model.

The fundamental assumption in the Cox model is that the hazards are proportional, which means that the effect of a covariate is constant over time. Violation of this assumption suggests that the effect of this covariate is time varying. In this study, the examination of the proportional hazards assumption was performed through examining Schoenfeld residuals plots. Proportional hazard is indicated by a horizontal line. To fit a Cox model with time-varying coefficients, we used both a continuous function and a step function.

RESULTS

Research Topic 1: Estimated Survival Rate of Transfer Students within Eight Semesters after Enrollment.

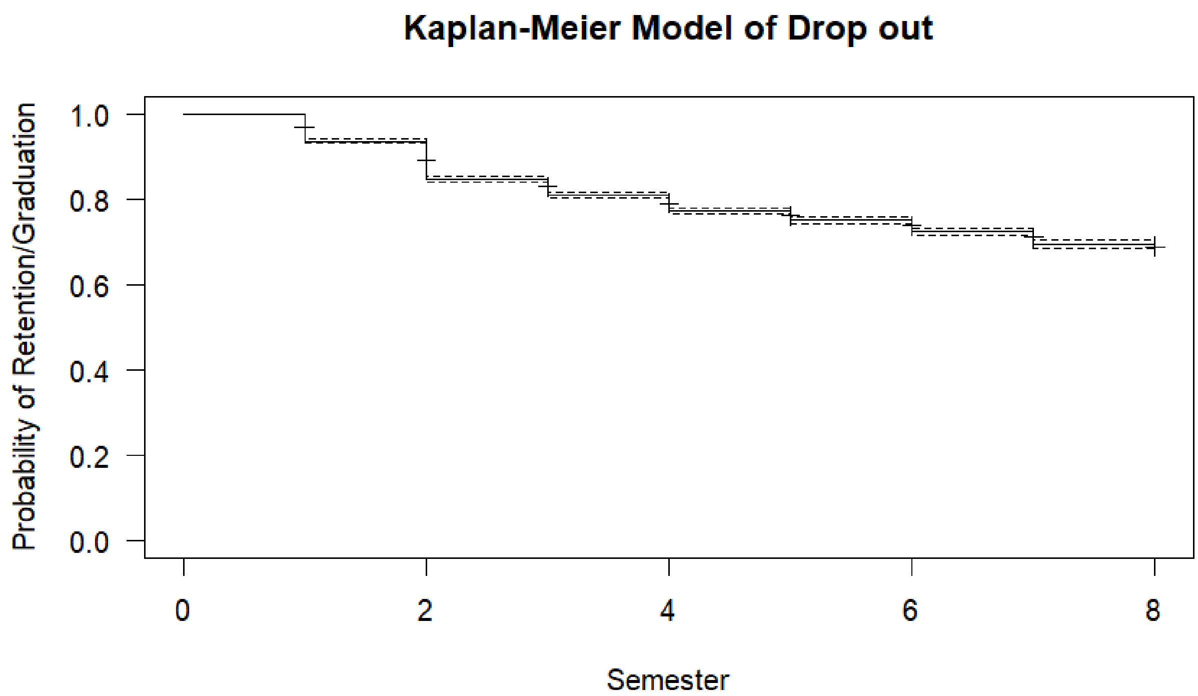
In survival analysis, the estimated survival probability represents the probability that a transfer student would persist after a given number of semesters. It was computed as the number of students who persisted after x semesters divided by the total number of students enrolled in the first semester. The scale is 0.00 to 1.00. Table 3 shows that the 95% confidence interval for the probability of a transfer student to persist after Semester 8 is between 67.1% and 69.2%. Figure 1 shows a Kaplan-Meier curve of the estimated persistence probabilities for all the transfer students in this study over eight semesters.

Table 3. Estimated Survival Probability and Hazard Rate by Number of Semesters Enrolled (N = 11,267)

Semester	Estimated survival probability	Lower 95% CI	Upper 95% CI	Hazard rate
1	0.936	0.932	0.941	0.064
2	0.847	0.840	0.854	0.095
3	0.810	0.802	0.817	0.044
4	0.772	0.764	0.780	0.047
5	0.751	0.743	0.759	0.027
6	0.724	0.716	0.733	0.036
7	0.695	0.686	0.705	0.040
8	0.681	0.671	0.692	0.020

Note: CI is confidence interval.

Figure 1. Kaplan-Meier Curve of the Estimated Persistence Probabilities

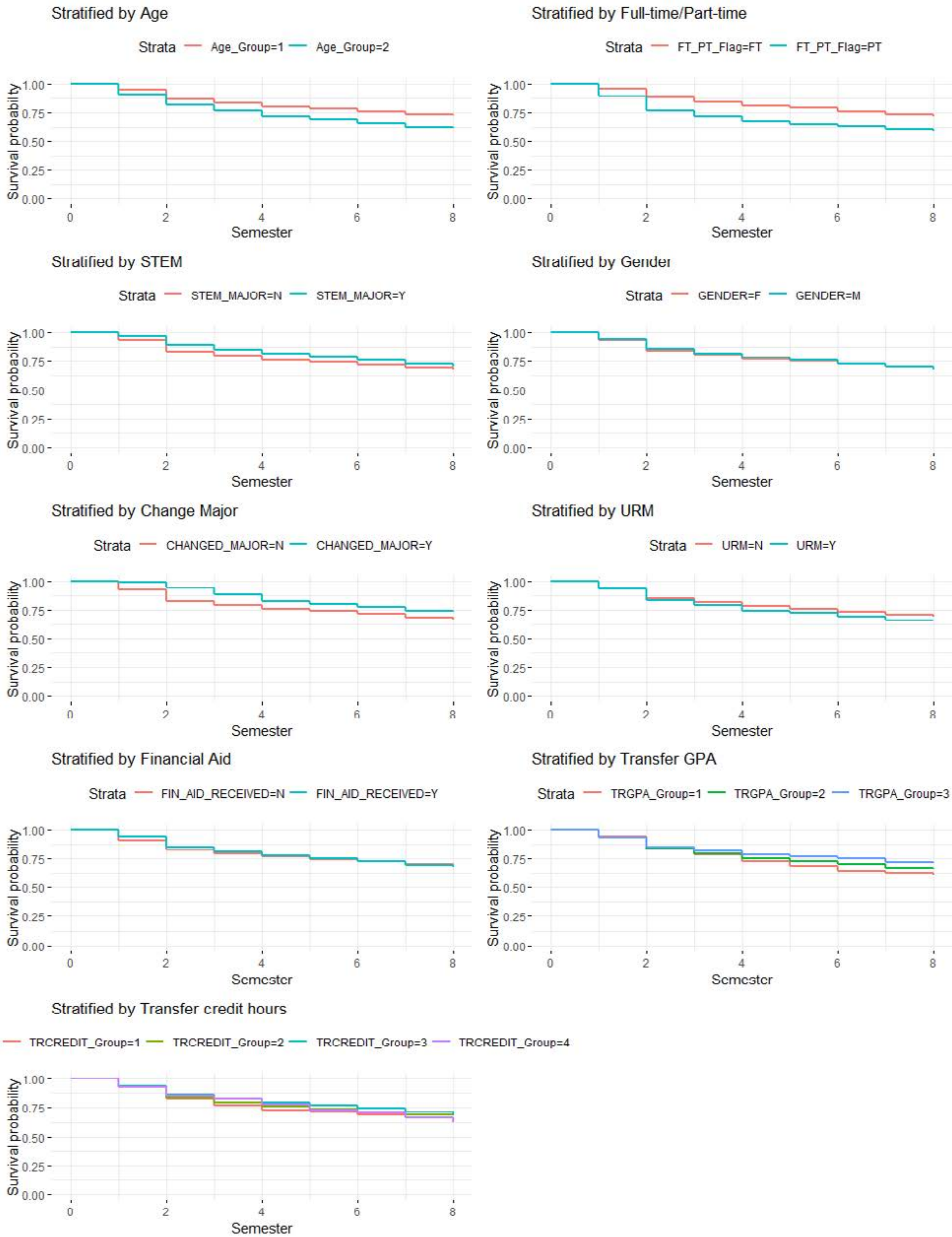


On the other hand, the hazard function is used to present the probability of an event occurrence at each period. In this study, we use the term "hazard rate" to refer to this probability. The hazard rates shown in Table 3 represent the probabilities that a transfer student would depart after x semesters. It was computed as the number of students who had departed after x semesters divided by the total number of students enrolled in x semester. The scale is thus 0.00 to 1.00. For example, for transfer students in this study, hazard rates were 0.064 and 0.095 after the first and second semesters of enrollment at the university, which are the two highest hazard rates among the eight semesters. After Semester 2 the hazard rates decreased and the changes in the rates were relatively small.

Research Topic 2: Survival Rates between Subgroups.

We used the stratified Kaplan-Meier method to estimate and visualize survival curves (see Figure 2) and the Gehan-Wilcoxon test to determine if there was a difference in the overall survival distributions between groups. The groups compared were based on age (24 and younger, over 24), majors (STEM, Non-STEM), change of major (Yes, No), transfer GPA (<2.5, ≥2.5 and <3, ≥3 and ≤4), transfer credit hours (<30, ≥30 and <60, ≥60 and <90, ≥90), financial aid (Yes, No), enrollment status (full time, part time), gender (female, male), and race/ethnicity (URM, Non-URM).

Figure 2. Stratified Kaplan-Meier Plot by Student Groups



The Kaplan-Meier plots for each group are presented in Figure 2. Gehan-Wilcoxon test results indicated that students who changed major were more likely to persist than those who did not change major (χ^2 (1)=37, *p*<.0001). Students who were in STEM majors were more likely to persist than those who were not in STEM majors (χ^2 (1)=19.1, *p*<.0001). URM students were more likely to drop out than non-URM students (χ^2 (1)=13, *p*=.0003). Students younger than 25 were more likely to persist than those above 25 years old (χ^2 (1)=124, *p*<.0001) and students with higher transfer GPAs were more likely to persist than those with lower transfer GPAs (χ^2 (2)=33.7, *p*<.0001). Full-time transfer students were more likely to persist than part-time students (χ^2 (1)=235, *p*<.0001). Survival distributions for the four transfer credit hours groups were significantly different (χ^2 (3)=18.6, *p*=.0003). Generally, the more transfer credits students brought in, the more likely they were to persist. However, after four semesters those students who had transferred in the highest number of credit hours were less, rather than more, likely to persist. Finally, no difference was found either between the survival rates of students who received financial aid and those who did not (χ^2 (1)=1.2, *p*=0.3), or between female students and male students (χ^2 (1)=0.7, *p*=0.4).

Research Topic 3: Size of the Effects of the Covariates on the Probability of Transfer Students' Retention and Graduation.

The Cox proportional hazard model was used to examine the effects of covariates on the probability of students' persistence. Covariates (see Table 2 for details) included age, major (STEM or not), major change, transfer GPA, transfer credit hours, financial aid, full-time or part-time status, gender, and race/ethnicity (coded as URM or Non-URM). The total sample size was 11,267 and the number of events (departures) was 3,080. A positive coefficient means lowered survival and a negative coefficient means increased survival.

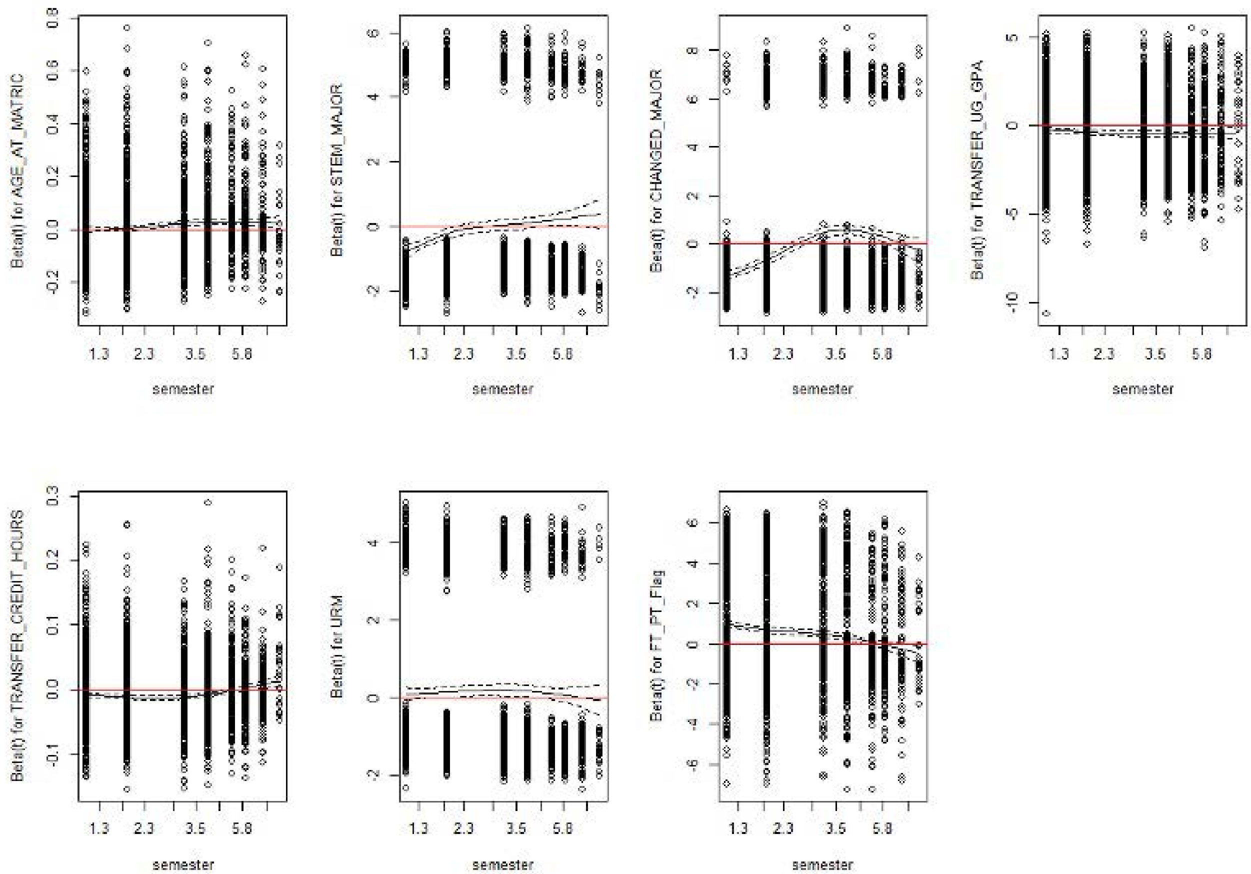
To optimize variable selection and check the fundamental assumption of the Cox model that the hazards were proportional, a Cox model with all covariables was run. We examined the p value and the Schoenfeld residuals plot of each variable. All covariates were significant at a .95 confidence level. Because the financial aid variable was not significant in the log-rank test of the stratified Kaplan-Meier model and had a much higher p value in the Cox model than all other variables, this variable was removed to optimize the model. The same was true for the gender variable. The results of the optimized model are presented in Table 4.

Table 4. Estimated Effects of Selected Variables on the Probability of Departure in the Optimized Cox Model

Term	Estimate	Std. Error	Statistic	p. Value	Exp (Estimate)
Age at Matriculation	0.014	0.003	5.641	<.001	1.014
STEM Major = Yes	−0.199	0.046	−4.290	<.001	0.820
Changed Major = Yes	−0.355	0.053	−6.646	<.001	0.701
UG GPA	−0.376	0.042	−8.917	<.001	0.686
Transfer Credit Hours	−0.008	0.001	−8.408	<.001	0.992
Part time = Yes	0.543	0.045	11.959	<.001	1.721
URM = Yes	0.134	0.042	3.212	<.01	1.143

The Schoenfeld residuals plots can help determine whether covariates are time varying. The plot of Schoenfeld residuals against time should not show a pattern of changing residuals for the covariate; that is, the smoothed plot should be flat and close to zero. If there is a pattern, that covariate is time dependent. Generally, a nonzero slope is an indication of a violation of the proportional hazard assumption. Figure 3 shows that the major (STEM vs. non-STEM) effect increased the first two semesters, then went flat in the 2nd year, and increased again after the 2nd year; the full-time/part-time effect constantly decreased over time; and the major change effect increased from matriculation to Semester 4 and then decreased. These variables obviously violate the proportional hazards assumption of the Cox proportional hazard regression since they are time varying. Thus, they should be investigated further.

Figure 3. Schoenfeld Residuals Plots



To fit a Cox model with time-varying coefficients, we used a stratified Cox proportional hazard model. The timeline was cut into three strata: Semesters 1 and 2, Semesters 3 and 4, and Semesters 5 through 8. We applied the strata function on STEM_MAJOR, CHANGED_MAJOR, and FT_PT_Flag covariates. The estimated effects of selected variables on the probability of departure in the final Cox model are presented in Table 5. Note that the estimate of AGE_AT_MATRIC, TRANSFER_UG_GPA, TRANSFER_CREDIT_HOURS, and URM covariates are averaged over the strata, while the STEM_MAJOR, CHANGED_MAJOR, and FT_PT_Flag covariates have estimates on each stratum.

Table 5. Estimated Effects of Selected Variables on the Probability of Departure in the Final Cox Model

Term	Estimate	Std. Error	Statistic	p. Value	Exp (Estimate)
AGE_AT_MATRIC	0.014	0.003	5.685	<.001	1.014
TRANSFER_UG_GPA	–0.373	0.042	–8.822	<.001	0.689
TRANSFER_CREDIT_HOURS	–0.008	0.001	–8.371	<.001	0.992
URM = Yes	0.132	0.042	3.185	<.01	1.142
STEM_MAJOR: strata(tgroup) tgroup=1	–0.501	0.068	–7.404	<.001	0.606
STEM_MAJOR: strata(tgroup) tgroup=2	0.021	0.085	0.241	*	1.021
STEM_MAJOR: strata(tgroup) tgroup=3	0.295	0.099	2.994	<.05	1.344
CHANGED_MAJOR: strata(tgroup) tgroup=1	–1.154	0.099	–11.711	<.001	0.315
CHANGED_MAJOR: strata(tgroup) tgroup=2	0.363	0.082	4.399	<.001	1.437
CHANGED_MAJOR: strata(tgroup) tgroup=3	0.009	0.111	0.083	*	1.009
FT_PT_Flag: strata(tgroup) tgroup=1	0.673	0.055	12.172	<.001	1.961
FT_PT_Flag: strata(tgroup) tgroup=2	0.506	0.079	6.413	<.001	1.659
FT_PT_Flag: strata(tgroup) tgroup=3	0.1206	0.102	1.183	*	1.128

* Indicates the variable is not significant at $p < .05$.

The Exp. (Estimate) column in Table 5 is the back-transformed coefficient of the covariates of focus. It is similar to the odds ratio concept in logistic regression. If the value is greater than one, the chance of an event occurring increases; if the value is less than one, the chance of the event decreases. Results show that, assuming equality of other hazard factors, all factors in the model are statistically significant. Specifically, for each additional year of age at matriculation (at baseline), departure hazard increases by 1% on average. For each one credit hour brought in, departure hazard decreases by 0.7% on average. For each one point of transfer GPA increase at baseline, departure hazard decreases by 31% on average. Additionally, from matriculation to Semester 2, departure hazard for STEM students is 60% of that for non-STEM students; the departure probability of STEM students increases over time, however, as shown by the coefficient changing from negative to positive. After four semesters, STEM majors are 34% more likely to drop out than are non-STEM majors. In their first two semesters, part-time students are 96% more likely to drop out than are full-time students, but this effect constantly decreases over time as indicated by the coefficient of FT_PT_Flag: strata(tgroup) changing from 0.67 to 0.12; that is, the departure probability of part-time students gradually decreases. From Semester 3 to 4, they are 66% more likely to drop out. After four semesters, there is no difference in the drop-out probability of part- and full-time students. Finally, the effect of changing major is significant from matriculation to Semester 4: Students who change their major in Year 1 are 68% less likely to depart within Year 1 than are students who do not change majors; from Semester 3 to 4, however, students who change majors are 44% more likely to drop out than those who did not change majors. After four semesters, there is no difference in the drop-out probability of those who change majors and those who do not because the *p*-value is much greater than .05.

DISCUSSION AND CONCLUSIONS

Few studies have used survival analysis to study transfer student persistence. To fill the gap, this study used survival analysis to investigate the persistence of transfer students during their (initial) 4 years at a transfer university. Our findings reveal critical insights into the factors affecting the persistence of these students. The probability of students persisting stands at 0.681 with a 95% confidence interval (0.671, 0.692). When analyzing specific subgroups, we observed several significant trends. For instance, transfer students who changed majors after transferring, those majoring in STEM fields, individuals below 25 years, those with a higher transfer GPA, and those transferring more credit hours all displayed higher persistence rates. Moreover, full-time students and non-URM students also showed a higher likelihood of persistence.

These findings replicate those of several prior researchers but conflict with others. The impact on transfer student persistence of credit hours transferred (Hutton, 2015; Luo et al., 2007), enrollment status (Hutton, 2015; Ronco, 1995; Wang, Wang, et al., 2017), and age (Murtaugh et al., 1999) were replicated. However, our study showed no distinction between the survival rates of students based on gender or financial aid received, which diverges from previous studies. For instance, Wang (2009) found that females had a higher probability of completing a bachelor's degree, echoing Ronco (1995) and Wang, Wang, et al. (2017) in the context of survival analysis. The nonsignificance of financial aid in our study also contrasts with Hutton (2015) who suggested that financial aid could impact persistence, albeit marginally.

The study is limited in a few ways. For example, additional demographic and academic variables could have been considered in the model such as first-term or 1st-year GPA. Perhaps more importantly, because the focus of a survival analysis is the passage of time, other time-varying covariates could have been included, such as GPA per semester or credit hours earned per semester. There are two kinds of time-varying covariates, and future studies should include both. One type of covariate changes value over time, and also changes over time in its impact on the outcome variable; the other does not change value over time but its effect on the outcome variable changes over time. The current study included no covariates of the first type. Finally, using a simplistic financial aid variable (FIN_AID_RECEIVED,Y, N) may have accounted for this variable not reaching significance and being omitted from the model. An alternative way of coding financial aid (e.g., as a continuous variable) or having more than one financial aid variable might have altered the results. Further research is warranted to help identify reasons for conflicting findings and to provide additional support for our assertion that survival analysis is a useful tool in understanding what factors help or hinder transfer student success.

There are implications in the current study for fostering transfer student success, defined as persistence in college. Providing academic and other types of support targeted specifically to transfer students and adult learners may prove beneficial. Advising students to maximize the number of transfer hours applied toward their intended major would likely improve graduation rates for these students. Advisors can work with transfer students to create clear academic pathways that consider their specific profiles, such as age, transfer credits, and ability to take a full-time course load. Our findings indicate that the impact of some variables changes over time, so interventions could be targeted at specific semesters to optimize impact. It is also the case that 4-year institutions might benefit from closer collaborations with community colleges, ensuring smoother academic transitions, aligning curricula, and providing shared resources and support for students.

With the declining number of high school graduates (Bransberger et al., 2020) and, thus declining number of first-time-in-college students, the recommendations above and other best practices in transfer student success (see, e.g., Smith et al., 2021) are important focal points for institutions wishing to maintain enrollment in the coming years. Fall 2023 data from the National Student Clearinghouse Research Center (NSCRC) show the number of new students who transferred into a new institution grew 5.3% compared to Fall 2022, with transfers representing 13.2% of all continuing and returning undergraduates (NSCRC, 2024). As the landscape of higher education continues to evolve, with shifting demographics and enrollment patterns, it becomes increasingly important to address the challenges faced by transfer students. The research presented in this study highlights the need for proactive measures to bridge the completion gap and to ensure that transfer students have equitable opportunities to attain their educational goals. Institutions that prioritize the success of transfer students will be better positioned to adapt to the changing educational landscape and maintain robust enrollment in the years to come.

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