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Predicting Pilot-in-training Success and Persistence in a United States University

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Commercial pilot numbers have been on a decline since 2009, while in parallel, pilot demands continue to rise. In order to close the gap, airlines and companies need a steady stream of pilots-in-training who have successfully graduated. However, collegiate flight training programs have had issues with low retention and low success rates of pilots-in-training. The need to understand how to retain students within collegiate flight programs and increase success rates is vital to fill the gaps present within the aviation industry. Past studies have investigated predictive factors for pilots-in-training graduation persistence and the time it takes to graduate yielding similar findings. Many factors have been identified as related to pilot-in-training success and persistence, the most common being high school GPA and cost. However, suggestions have been presented as variables of interest to examine for future studies, such as the effect of different types of flight postponements. The research study conducted expanded the knowledge regarding variables that predict or contribute to pilot-in-training success in a collegiate aviation flight degree program, examining graduation persistence and time to graduate. An archival data of 262 pilot-in-training students were used to explore the relationship between the 19 predictors, graduation persistence, and time to graduate. Several variables had significant relationships with both Time to Graduate and Persistence Before Dropout, including Age, Number of Transfer Credits, Class Load, and Pass Rates in Aeronautics Classes. Additionally, Time to Graduate had a significant relationship with Academic Success in Aeronautics Classes and Maintenance Postponements per Semester. Persistence Before Dropout had a significant relationship with Instructor Changes, Instructor Postponements, and Weather Postponements.

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Introduction

Background

The aviation industry continues to grow as air travel becomes safer and more affordable (Airlines for America, 2019). Airline passenger traffic and revenue passenger miles (RPM) have increased significantly, with 2018 seeing an increase of over 109 million RPM in the United States between 2015 and 2018 (Airlines for America, 2018; Lutte, 2019). Unfortunately, the increases seen for passengers has not mirrored in commercial pilots, as the pilot numbers that would be needed to fulfill passengers' needs are not there (Caraway, 2020; Federal Aviation Administration, 2019; Klapper & Ruff-Stahl, 2019) in parallel to the rising increase in pilot demand (CAE, 2017; Lutte, 2018). Higgins et al. (2013) projected that U.S. airlines could face a pilot shortage between 2013 and 2031 as this could go as high as 35,000 pilots. Although the COVID-19 pandemic decreased pilot-in-training numbers for a period of time, a survey administered to aviation flight schools around the world found that pilot-in-training numbers are back to 94 percent of their pre-COVID-19 activity levels and still rising (Flight Logger, 2021; Redbird Flight Simulations, 2021). The aviation industry is expected to rebound from setbacks caused by COVID-19, and the substantial need for pilots is expected to continue (Redbird Flight Simulations, 2021). In order to close the gap between passenger demand and the shortage of commercial pilots, airlines and companies need a steady stream of successfully graduating pilots-in-training. However, collegiate flight training programs have had issues with low retention, and low success rates of pilots-in-training (De Montalk, 2000; Leonard, 2018).

There is a need to understand how to retain students within collegiate flight programs and increase success rates to fill the gaps present within the aviation industry. A limited number of studies in the past have investigated predictive variables related to pilots-in-training success such as flight costs, class load, and academic success in flight. Patterns have emerged; however, more research is needed examining these variables together to further understand their relationship to persistence before dropout and the time it takes to graduate. The studies associated with predictor variables of pilot-in-training graduation success are presented in the following paragraphs. Leonard (2018) examined student success using Time to Graduate, measured as whether they graduated in 48 months or longer, and cumulative GPA, measured as the overall GPA at the end of the four years in a collegiate aviation program. Leonard framed the research question based on Astin's Input, Environment, and Output model (1970, 1984). A multiple regression was used to analyze 3,100 students registered in different aviation majors at the University of North Dakota during the 2016-17 academic year. The results of the study indicated that there was a significant relationship between credit loads, which were defined as academic intensity and degree attainment. Students who registered for higher credit loads were more likely to graduate in 48 months compared to students who took fewer credits each year on average. Additionally, working as a flight instructor increased the likelihood of graduating in 48 months. Leonard proposed that students who take more credit hours and work as flight instructors are spending more time surrounded by students who are going through similar experiences and can benefit from constant exposure.

McFarland (2017) conducted a correlation analysis to investigate the relationship between pre-entry and flight training attributes of students as predictors of success in a Flight Training program. Three construct groups were used: (a) an academic construct measured using test scores; (b) a cognitive construct using cognitive tests; and (c) a performance construct consisting of flight course grades and days to course completion. A sample of 242 students who completed a private pilot flight course was utilized. Results were consistent with collegiate math and/or physics scores, high school GPA, and ACT scores positively correlating with the successful completion of the private pilot course. Performance in flight courses was also found to be significantly correlated with successful completion of the private pilot course. When examining the relationship between the cognitive constructs and performance in flight courses, no significant relationship was found. McFarland suggested that reviewing performance in flight courses during the beginning of the program would help identify at-risk students early enough to intervene. The findings of the study also suggested that a decrease in the student-to-instructor ratio facilitated a better student retention rate in the flight program.

Bjerke and Healy (2010) examined pre-entry attributes as predictors of students' persistence and academic success in a Flight Training program. Persistence was measured as students who continued from the spring into the subsequent fall semester, and academic success was measured using GPA from the term. The study used archival data from 390 full-time students enrolled in a public, four-year, research-intensive university with commercial aviation as their declared major. The sample consisted of two cohorts, one beginning in the fall of 2006, and the other beginning in the fall of 2007. The following predictor variables were used in the study: Age, sex, ethnicity, high school GPA, ACT score, math ACT score, verbal ACT score, family's gross income, father's education level, mother's education level, and admitted credit hours. A multiple regression analysis was used to investigate the relationship between pre-entry attributes and the two criterion variables. Pre-entry attributes accounted for 9.6% of the variance in the students' persistence, with high school GPA as the most significant predictor. Variables such as age (r = .04), admitted credit hours (r = .10), and family's gross income (r = .42) were positively related to persistence. The results also indicated that the pre-entry attributes accounted for 32.3% of the variance in academic success. High school GPA (r = .47), admitted credit hours (r = .05), and ACT math scores (r = .16) had a significant and positive relationship with academic success. However, sex had no significant relationship with students' persistence and academic success. The findings suggest that older students, those who come into the program with more credit hours, and students whose families have higher gross incomes would have higher persistence in a collegiate aviation program. Additionally, those with higher high school GPAs, higher credit hours upon being admitted to the program, and higher ACT math scores were likely to have higher academic success.

The Government Accountability Office (GAO, 2018) investigated the variables contributing to the ability of 147 flight schools to produce professional pilots in the United States. GAO reviewed the following data from flight schools offering professional flight degree programs: degree completion for the 2015-16 school year, the FAA's data on flight schools' enrollment, the certified flight instructor data, the number of pilots in different categories (e.g., flight instructor and recreational), and new pilot certificates issued. Thirty-five representatives from flight schools, airports, airline personnel, FAA officials, and flight instructors were interviewed. The results of the study indicated that the high cost of training and low flight-instructor retention were the key challenges affecting flight schools' ability to produce professional pilots. Additionally, it was determined that both scheduled and unscheduled aircraft maintenance could also reduce the ability of flight schools to train flight students.

The Airline Owners' Pilot Association (AOPA, 2010) conducted a survey to investigate the variables that could improve student success rates in flight programs. The study used a mixed-methods approach. First, a qualitative survey asking participants to rate various attributes, such as instructor effectiveness, scheduling, and costs, was disseminated to create a list of variables that would lead to optimal Flight Training performance and increase the student success rate. Second, quantitative research was conducted to identify the perceptions of student pilots and flight instructors regarding the list of variables collected by the qualitative survey. The study used a sample of 1,000 students and flight instructors (750 students, 250 flight instructors). A list of 67 variables (attributes) identified through the qualitative analysis was divided into four groups based on the quantitative analysis: education quality, customer focus, community, and information sharing. Education quality consisted of instructor support, instructor effectiveness, and organized lessons. Customer focus consisted of variables such as flight costs, scheduling, and aircraft quality. The community consisted of certifications for student achievement and aviation environment. Information sharing consisted of variables such as success rates, estimated time, costs, and instructor experience level. The resulting participant responses indicated that improving flight instructor and student relationships would increase flight program experience and student success rates. Additionally, the results indicated that scheduling lessons in advance and being flexible would help in the Flight Training experience.

This extant research, though limited, suggests that there is a range of different predictor variables that likely impact Persistence Before Dropout and graduation success. It is also apparent from these findings that additional research is needed to confirm which variables are the most influential. The previous studies guided the research effort in many ways. The results of Leonard's (2018) study indicated that there was a significant relationship between higher credit loads and degree attainment as well as working as a flight instructor and graduating in 48 months. Therefore, the average class load per semester was examined in the current study to further explore this relationship. McFarland (2017) found a positive correlation between standardized test scores and completion of the private pilot course. Performance in flight courses was also positively correlated with the completion of the private pilot course. Therefore, the current study included a standardized test score variable and flight training performance variable. Bjerke & Healey (2010) found that age, admitted credit hours, and family's gross income were positively related to persistence. Further, high school GPA, admitted credit hours, and ACT math scores had a significant and positive relationship with academic success. Therefore, age, socioeconomic status, transfer credits, and academic variables such as GPA in flight and aeronautics courses were included. The results of the research conducted by GAO suggested that training costs, low flight-instructor retention, and aircraft maintenance were key in affecting pilot-in-training numbers. Therefore, the current study included variables for flight cost, instructor changes, and maintenance postponements. Finally, research by the AOPA suggested that improved flight instructor and student relationships could increase student success rates. The results also indicated that scheduling lessons in advance and flexibility would help in the flight training experience. Therefore, the current study examined instructor changes, student postponements, and flight instructor postponements.

Methodology

The purpose of the current research effort was to expand the knowledge regarding variables that predict or contribute to pilot-in-training success in a collegiate aviation flight-degree program by examining pilots-in-training persistence before dropping out and the time it takes to graduate. An ex post facto design was conducted using 19 predictor variables in five different functional sets. Set A = individual difference variables, Set B = involvement variables, Set C = achievement variables, Set D = instructor interaction variables, and Set E = flight postponement variables (see Table 1 for all variables within each set). The variables in each set were found to have a relationship with the dependent variables of Time to Graduate or Persistence Before Dropout for pilots-in-training.

Research Questions

There were two primary research questions (RQ):

> RQ 1: What is the relationship between variables related to student individual differences, involvement, achievement, instructor interactions, flight postponements, and time to graduate from a collegiate aviation training program?
>
> RQ 2: What is the relationship between variables related to student individual differences, student involvement, student achievement, instructor interactions, flight postponements, and persistence before dropout from a collegiate aviation training program?

Participants

Archival data were obtained from the Office of Institutional Research (OIR) at a Part 141 Collegiate program in the Southeastern U.S. for all flight students majoring in Aeronautical Science and Aviation Management with flights from 2010 until 2019. For the purpose of the current study, only student data between 2010 and 2016 were included in the dataset. This range ensured that all the students who were included in the analysis had been enrolled in the degree program for at least four years. The first regression was conducted for Time to Graduate and included a sample of n = 141 flight students. The second regression was conducted with Persistence Before Dropout as the dependent variable and included a sample of n = 121 flight students.

Power Analysis

An a priori power analysis was run using G* Power (Faul et al., 2007) for an F-test, using a multiple regression based on the five sets of variables: Power analysis parameters included an α = 0.05, with a medium effect size of .15 (Cohen et al., 2003) and 80% power. Based on the

G*Power results, it was determined that a minimum sample size of 163 participants was necessary to detect a medium effect size in the population. Unfortunately, our sample did not meet the minimum sample size requirements indicated by G*Power. However, similar correlational studies have reported a coefficient of determination (R^2) of more than .30 (Leonard et al., 2018), corresponding to a large effect, given that we had an R^2 of .52 for Persistence Before Dropout and an R^2 of .60 for Time to Graduate, we were comfortable moving forward with the analysis.

Experimental Design and Variables

The current study used a predictive correlational design and two hierarchical regressions to investigate the relationship between the five sets of predictor variables and their relationship with two different criterion variables: Persistence Before Dropout and Time to Graduate. The Persistence Before Dropout variable was calculated by taking the number of semesters a student completed out of the total expected academic semesters in the major (i.e., eight semesters). The Time to Graduate variable was measured as the number of semesters it took a student to graduate. The independent variables were selected and categorized into five sets based on the literature and anecdotal reports from flight instructors. Categorical variables were coded using a dummy coding strategy. Variables are presented in Table 1 and described in the following section.

Set A included eight individual difference variables. There were five continuous and three categorical variables. Age was a continuous variable, and socioeconomic status was a continuous variable measured using the financial aid received by the student in total dollars. Cognitive ability was measured as a continuous variable using a composite of two standardized test scores (SAT and ACT). Major was a categorical variable, students whose major was Aeronautical Science with Flight were represented as 0, and Aviation Management with Flight was represented as 1. The flight costs variable was measured using the total flight fees paid by the student during their time enrolled in the university and was presented in two ways as the variability in the number of semesters for the Persistence Before Dropout variable had a high variability with respect to the number of semesters students persisted. Specifically, we chose to categorize the flight costs based on the flight line's minimum threshold costs for each academic year. For the first regression in which Time to Graduate was the dependent variable, Flight Cost was a continuous variable. For the second regression in which Persistence Before Dropout was the dependent variable, Flight Cost was a dummy coded categorical variable with three categories (high, medium, and low) to allow high and medium Flight Costs to be compared to Low Flight Costs. High, Medium, and Low Flight Costs were calculated using the university flight line fees and policies posted on their website. Once calculated, two standard deviations below this value and two standard deviations above this value were used to create a minimum and maximum cost a student could have during their first, second, third, and fourth year in flight school. For example, the estimated flight cost for the first year was $23,759. Therefore, any student who paid between $18,000 to $21,000 fell into the Low Flight Cost category. Students who paid between $21,000 and $24,000 fell under the Medium Flight Cost category, and any price above $24,000 was considered to be High Flight Cost. Certification was measured by whether the student came in with their private pilot license or not. Finally, the Transfer Credits variable was measured using the total number of credits transferred into the program by the student.

The variable in Set B was measured in the following manner: Class Load is a continuous variable that was measured by calculating the average class load per semester. The variables in Set C were represented in the following manner: Pass Rate was a continuous variable represented by the percentage of aeronautics classes passed based on the total number of classes taken. Academic Success in Aero Classes was a continuous variable represented by the GPA of all aeronautics classes combined. Academic Success in Flight Classes was a continuous variable represented by the GPA of all flight classes combined.

The variables in Set D were represented in the following manner: Instructor changes were a continuous variable, representing the total number of different flight instructors the students trained with while obtaining their certificates. Flight Training performance was a continuous variable measured using the percentage of passed check rides based on total check rides. Set E consisted of five flight postponement variables, including Instructor Postponements, Student Postponements, Weather Postponements, Maintenance Postponements, and Other Postponements. Each postponement variable was a continuous variable in which the number of relevant postponements was averaged per semester.

Analysis

Preliminary Analysis

Outliers were removed based on studying jackknife distances and visual inspections of scatterplots for each variable. One outlier from each regression was removed based on these analyses. The final sample size for the Time to Graduate model was 140 participants, and the final sample size for the Persistence Before Dropout model was 120 participants.

Table 1
Independent Variable Sets and Criterion Variables in the Current Study

Sets/Independent Variables	Measure Description
Set A = Individual Difference Variables	
X_1 = Sex	X_1 is a categorical variable, self-reported sex
X_2 = Age	X_2 is a continuous variable, student age upon entry
X_3 = Socioeconomic Status	X_3 is a continuous variable, the dollars of financial aid
X_4 = Cognitive Ability	X_4 is a continuous variable, SAT/ACT composite of scores
X_5 = Major	X_5 is a categorical variable, one of two Aeronautics majors
X_6 = Flight Costs	X_6 is a continuous variable, total flight fees paid for Time to Graduate
	X_6 is a categorical variable with three levels (high, medium, and low) for Persistence Before Dropout
X_7 = Certification	X_7 is a categorical variable, flight certifications upon entering program
X_8 = Transfer Credits	X_8 is a continuous variable, number of transfer credits
Set B = Involvement Variables	
X_9= Class Load	X_9 is a continuous variable, average class load per semester
Set C = Achievement Variables	
X_{10} = Pass Rates	X_{10} is a continuous variable, percentage of Aero classes passed
X_{11} = Academic Success in Aero Classes	X_{11} is a continuous variable, Aeronautics class GPA
X_{12} = Academic Success in Flight Classes	X_{12} is a continuous variable, Flight class GPA
Set D = Instructor Interaction Variables	
X_{13} = Instructor Changes	X_{13} is a continuous variable, average number of instructor changes per semester
X_{14} = Flight Training Performance	X_{14} is a continuous variable, percentage of passed stage checks
Set E = Flight Postponement Variables	
X_{15} = Instructor Postponements	X_{15} is a continuous variable, average number of instructor postponements per semester
X_{16} =Student Postponements	X_{16} is a continuous variable, average number of student postponements per semester
X_{17} = Weather Postponements	X_{17} is a continuous variable, average number of weather postponements per semester
X_{18} = Maintenance Postponements	X_{18} is a continuous variable, average number of maintenance postponements per semester
X_{19} = Other Postponements	X_{19} is a continuous variable, average number of other postponements per semester
Dependent Variables	
Y_1 = Time to Graduate	Y_1 is a continuous variable, the number of semesters it took for a student to graduate
Y_2 = Persistence Before Dropout	Y_2 is a continuous variable, the percentage calculated based on the number of semesters in a flight major out of the total academic semesters (i.e., eight)

Regression Assumptions

Next, both models were tested for the six regression assumptions. Assumption 1, the assumption of linearity, was not met by the Time to Graduate model. To resolve this issue, we built the bi-variate scatter plots for each independent and dependent variable. We found that Class Load was not linearly related to the Time to Graduate model. Based on Cohen et al. (2003), squared and cubic models were created for the Class Load variable to facilitate the interpretation of a non-linear slope. The persistence model met the linearity assumption. For assumption 2, the correct specification of the IVs, we chose a *p-value* threshold of 0.2, which means all the variables that had a *p*-value less than 0.2 were included in the final model. For the Time to Graduate regression, only seven out of the 17 variables met these criteria and were utilized in the primary analysis, including Age, Major, Transfer Credits, Class Load, Pass Rates, Academic Success in Aero, and Average Number of Maintenance Related Postponements per Semester. For the Persistence Before Dropout regression, nine out of the 17 variables met these criteria and were utilized in the primary analysis, including Age, High Flight Costs, Low Flight Costs, Class Load, Pass Rates, Instructor Changes, Instructor Postponements, Student Postponements, and Weather Postponements. Both the models met assumption 3, perfect reliability; assumption 4, homoscedasticity of residuals; assumption 5, independence of residuals; and assumption 6, normality of residuals.

Primary Analysis

Two hierarchical regressions were conducted with Persistence Before Dropout and Time to Graduate as the criterion variables and 19 predictor variables divided into five sets as described in Table 1. Based on the literature, a prioritized set entry order of A-B-C-D-E was utilized. In Table 2, we present the final model for Time to Graduate, which had an overall R^2 = .60, meaning 60% of the variance in Time to Graduate is collectively explained by individual difference variables, involvement variables, achievement variables, and flight postponement variables. The overall model was significant, $F(7, 132) = 27.71$, $p < .001$, and included significant independent variables of Age, Transfer Credits, Academic Success in Aero Classes, and Maintenance Postponements. When individual difference variables were added into the model, the overall $R^2 = 0.19$, with Age and Transfer Credits contributing a significant amount of variance, indicating individual difference variables uniquely contributed 19% of the variance in Time to Graduate. When involvement variables were added into the model, the overall $R^2 = 0.55$, indicating involvement variables uniquely contribute 36% of the variance in Time to Graduate with one significant variable, Class Load. When achievement variables were added into the model, the overall R^2= 0.59, indicating that achievement variables uniquely contributed approximately 4% of the variance in Time to Graduate, including one significant variable, Academic Success in Aero Classes. When flight postponement variables were added to the model, the overall $R^2 = 0.60$. Average Flight Postponement uniquely contributed about 1% variance in the Time to Graduate, including one significant variable, Maintenance Postponements per Semester.

Table 2
Final Hierarchical Model of Time to Graduate

Predictor	Model 1B	Model 2B	Model 3B	Model 4B	
				B	**95% CI**
Constant	4.7***	15.9***	26.9***	26.91**	[12.41,41.42]
X2 = Age	0.14**	0.08*	0.09*	0.08*	[0.001,0.153]
X5 = Major Code	0.15	0.52*	0.39	0.40	[-0.04, 0.83]
X8 = Number of Transfer Credits	0.02**	0.01*	0.01*	0.01*	[0.001, 0.02]
X9 = Class Loads		-0.63***	-0.65**	-0.66*	[-0.77, -0.54]
X10 = Pass Rates in Aero Classes			-13.52	-13.17	[-28.05,1.70]
X11 = Academic Success in Aero Classes			0.73**	0.74**	[0.23, 1.24]
X18 = Maintenance Postponements				0.74*	[0.04, 1.44]
Statistical Results					
R^2	0.19***	0.55***	0.59***	0.60***	
F	10.52	42.17	30.88	27.71	
Delta R^2		0.36***	0.04***	0.01	
Delta F	0.19***	0.55***		0.60	

Note. *Indicates p-value is significant at 0.05. ** Indicates p-value is significant at 0.01. *** Indicates p-value is significant at 0.001.

In Table 3, we present the final model for Persistence Before Dropout, which had an overall $R^2 = 0.52$, meaning 52% of the variance in Persistence Before Dropout is collectively explained by individual difference variables, involvement variables, achievement variables, instructor interaction variables, and flight postponement variables. The overall model was significant, $F(9, 111) = 16.63$, $p < .001$, and included significant independent variables of Age, Transfer Credits, Academic Success in Aero, and Maintenance Postponements per Semester. When individual difference variables were added into the model, the overall $R^2 = 0.08$., with Age being a significant variable.

Table 3
Final Hierarchical Model for Persistence Before Dropout

Predictor	Model 1B	Model 2B	Model 3B	Model 4B	Model 5B	
					B	95% CI
Constant	8.55***	17.8***	14.99***	16.79***	18.01***	[11.22, 24.80]
X_2 = Age	-0.16**	-0.23	-0.22***	-0.17**	-0.205***	[-0.31, -0.10]
X_6^a = High Flight Costs	0.74	0.90	0.316	2.1**	3.81***	[2.27, 5.35]
X_6^b = Number of Transfer Credits	1.1	1.12	0.646	1.55*	2.28*	[1.08, 3.5]
X_9 = Class Load		-0.49*	-0.49*	-0.53**	-0.53*	[-0.85, -0.27]
X_{10} = Pass Rates in Aero Classes			3.29*	3.03**	3.15**	[1.14, 5.16]
X_{11} = Instructor Changes				-1.72***	-1.31***	[-1.18, -0.80]
X_{15} = Instructor Postponements					-0.26*	[-0.49, -0.03]
X_{16} = Student Postponements					0.15	[-0.06, 0.38]
X_{17} = Weather Postponements					-0.32	[-0.52, -0.12]
Statistical Results						
R^2	0.08*	0.12**	0.17***	0.45***	0.52***	
F	3.38	3.92	4.65	15.06	16.63	
Delta R^2		0.04***	0.5***	0.28***	0.07***	
Delta F						

Note. * Indicates *p*-value is significant at 0.05. ** Indicates *p*-value is significant at 0.01. *** Indicates *p*-value is significant at 0.001.

When involvement variables were added into the model, the overall $R^2 = 0.12$, indicating involvement variables uniquely contributed 4% of the variance in Persistence Before Dropout with one significant variable, Class Load. When achievement variables were added to the model, the overall $R^2 = 0.17$, indicating that achievement variables uniquely contributed about 5% of the variance in Persistence Before Dropout with one significant variable, Academic Success in Aero Classes. When instructor interaction variables were added into the model, the overall $R^2 = 0.45$, indicating that instructor interaction variables uniquely contributed about 28% of the variance in Persistence Before Dropout with one significant variable, Instructor Changes. When flight postponement variables were added to the model, the overall $R^2 = 0.52$. Flight postponement variables uniquely contributed about 7% variance in Persistence Before Dropout, with two significant variables, Instructor Postponements and Student Postponements per Semester.

Discussion

The results of the current study support previous findings and provide support for variables related to individual differences, involvement, achievement, instructor interaction, and flight postponements being predictive of pilot-in-training success. Several variables had significant relationships with Time to Graduate and Persistence Before Dropout, including Age, Number of Transfer Credits, Class Load, and Pass Rates in Aeronautics Classes. Additionally, Time to Graduate had a significant relationship with Academic Success in Aeronautics Classes and Maintenance Postponements per Semester. Persistence Before Dropout had a significant relationship with Instructor Changes, Instructor Postponements, and Weather Postponements. These relationships will be examined in detail below.

Individual Difference

A significant and positive relationship was found between Age and Time to Graduate. Specifically, for every 10-year increase in age, on average, Time to Graduate increased by one semester. Similarly, for every 10-year increase in age, on average, Persistence Before Dropout decreased by half a semester. This finding suggests that as age increases, pilots-in-training are less likely to graduate within eight semesters and are less likely to persist. This finding may be due to changes in responsibilities that accompany increases in age, such as family and work responsibilities which limit the ability to dedicate time to studies and can result in part-time enrollment (Bjerke & Healey, 2010; Shapiro et al., 2016). Alternatively, this may be influenced by the smaller number of students in the sample who were older than the traditional collegiate age range (i.e., 18-22 years old) or differences in the types of students who are non-traditional (i.e., delayed college, changed careers, returned to college after military service). With this in mind, it may be beneficial to make older students more aware of the program requirements and time expenditure necessary to complete the program within eight years. This finding is not consistent with some of the literature (e.g., Leonard, 2018; Waldman & Avolio, 1986). Leonard (2018) found no relationship between age and graduating within 48 months. The difference may be due to a lack of variability in the age of their sample size as their mean was 18, and their standard deviation was 0.5, whereas the current sample had a mean of 25 and a standard deviation of 3.2 for the Time to Graduate regression and 5.2 for the Persistence Before Dropout regression. Bjerke and Healy (2010) had similar findings, in which age was positively correlated to persistence from year one to year two. However, just as in Leonard (2018), the variables were examined in a different light that is they did not look at it across semesters.

A significant relationship was also found between High Flight Costs and Persistence Before Dropout. Students with High Flight Costs persisted four semesters longer than students with Low Flight Costs. High flight costs were, costs two standard deviations higher than the average cost that a student could pay based on flight line fees and policies. Low flight costs were two standard deviations lower than the average flight cost that a student could pay based on flight line fees and policies. Students with Medium Flight Costs (i.e., the average flight cost based on flight line fees and policies) persisted for two semesters longer than students with Low Flight Costs. This suggests that the students who paid high flight costs persisted longer than the students who paid medium and low flight costs. This finding may point to the sunken cost fallacy (Friedman et al., 2007), as students are focusing on the time and money already invested and do not want it to go to waste, so they persist. Another reason may have to do with the population from which the sample was derived. The study university has a large international student population, and anecdotal reports from advisors and certified flight instructors point to the fact that pressure from families back home may encourage students to persist with the flight major that they initially started with, and this explanation has also been supported by previous scientific literature (Andrade, 2008; Kwai, 2010).

A positive and significant relationship was also found between the number of transfer credits a student transferred in when they started the program and the Time to Graduate. For every additional 100 credits transferred into the university, Time to Graduate increased by one semester. This finding is not in line with extant research. Bjerk and Healy (2010) found that the higher the transfer credits, the higher the academic success, which does not align with the current findings. A potential explanation for this is that many individuals transfer in credits from a different major, but not all credits can be utilized towards the flight degree. Therefore, additional credits need to be taken into account based on the number of credits counting towards the flight degree program.

There were several individual difference variables that were not found to have significant relationships. No relationship was found between Sex and either Time to Graduate or Persistence Before Dropout. Studies examining sex and pilots-in-training have found similar results (Bjerke & Healy, 2010; Leonard, 2018); however, these results have not been found in non-aviation contexts (Peltier et al., 2000; Trippi & Baker, 1989;). This may be due to the similarities in personality between males and females in the aviation industry, a consistent finding that is not replicated in the general population and is an influencing factor in aviation training outcomes (Chaparro et al., 2020). No significant relationship was found between Major and the two dependent variables. This may be due to the inclusion of students from the two flight majors, aeronautical science and aviation management, being too similar. Interestingly, no relationship was found between Flight Costs and Time to Graduate, which again may point to the university at which the study was conducted, as instructors and advisors stated that many of the international students were not concerned with the money aspect as long as they graduated from the program. This is an interesting finding from the perspective of reverse causation, where the longer it takes one to graduate because of the flight, the more they pay toward tuition. This finding points to what is commonly referred to as the “sunk cost fallacy,” as students have invested so much time and money that they are unwilling to stop in the hopes that they can turn things around (Siegel, 2011).

No relationship was found between Transfer Credits a student held and Persistence Before Dropout: therefore, this may not be a factor that causes students to persist in a program. A possible explanation for this finding could be that when a student transfers in with more credits, they have less time to finish the degree and, therefore, may not encounter problems of dropout before finishing the degree. For example, if a student is transferring with 60 credits, the student only needs, on average, two years to finish the remaining 60 credits to graduate; therefore, both the short duration and less number of credits will not significantly impact students’ Persistence Before Dropout. Based on the finding, we recommend that it might be beneficial if flight programs orient the students transferring in with a previous degree with oversight to help them graduate on time. Those students should be made aware that their Time to Graduate may take around a semester more, depending on their situation.

Involvement

When examining involvement, specifically the Class Load variable, a polynomial relationship resulted between Time to Graduate and Class Load. Time to Graduate increased until approximately 12 credit hours per semester, where it then decreased until 15 credit hours per semester; after 15 credit hours, the Time to Graduate increased again. The findings of the current study were consistent with extant research (Attewell & Monaghan, 2016; Attewell et al., 2012; Huntington-Klein & Gill, 2020) that suggests there is an optimal class load, under which students may not be taking enough classes to stay on track, and over which student load may be overtaxing and extend their time due potentially to failing classes. When examining Class Load and Persistence Before Dropout, a negative relationship was found. For every six additional credits per semester, Persistence Before Dropout decreased, on average, by one semester. This may point to the threshold for too many classes before an individual's persistence is affected. Based on the findings, we recommend that universities encourage students to take between 12 and 15 credits during the spring and fall semesters.

Achievement variables

A positive relationship between Pass Rates and Persistence Before Dropout was found. For every 30% increase in Pass Rates, on average, Persistence Before Dropout increased by one semester. The findings were consistent with the study conducted by Clery and Topper (2008) that illuminated how students who do well are likely to persist in the program longer than those with low pass rates. A positive relationship also existed between student Academic Success in Aeronautics Classes and both Time to Graduate and Persistence Before Dropout, indicating that for every 1-point increase in GPA, Time to Graduate increases by approximately one semester. For every 30% increase in aeronautics class Pass Rates, on average, Persistence Before Dropout increased by one semester. These findings may seem unintuitive; however, many high-performing students pursue one or more minors. Pursuing a minor requires students to take additional courses, such as graduate courses, which could impact Time to Graduate (Clery & Topper, 2008).

No relationship was found between Pass Rates and Time to Graduate, potentially due to the fact that high performers often take on a minor or enroll in additional classes, which may add on time, whereas those who are doing well and not taking extra classes may actually graduate early, making that relationship difficult to discern.

Instructor Interactions

A negative relationship was found between Instructor Changes and Persistence Before Dropout. For every two instructor changes per semester, Persistence Before Dropout decreased by one semester. A plausible explanation for this finding could be the CFIs being international students. International students, after obtaining a flight instructor license, work towards their commercial license, which requires 1,500 hours of flying time. Being a CFI, once they finish 1,500 hours of flying, they may leave the CFI job to start working as an airline pilot. In the context of this study, students who work with a particular CFI for a few semesters may lose interest if their CFI leaves the job. This may be due to the rate at which instructor changes tend to occur by either student's progress through check rides versus an issue with an instructor. Unlike other university programs, the classroom for a pilot is more high-risk and requires a feeling of comfort with their instructors, a constant change not related to check rides may not allow for that trust to build, leading to decreased persistence.

No relationship was found between Flight Training performance and the two dependent variables. This may be due to many factors, such as the fact that different instructors grade students in a different manner, and each student is graded by multiple instructors. Additionally, students can receive different flight certifications, leading to differing levels and opportunities for performance results. No relationship was found between Instructor Changes per semester and Time to Graduate, potentially due to the fact that instructor changes happen throughout the program in part because instructors have different certification levels, which means that they can only teach certain flight courses. Thus, it would not likely affect the time it takes an individual to graduate. However, this is not the case with persistence.

Flight Postponements

Weather and Instructor postponements had a negative relationship with Persistence Before Dropout. That is, for every three additional Weather and Instructor Postponements per Semester, Persistence Before Dropout decreases by one semester. A plausible reason for this finding could be the students' locus of control and motivation level. This may point to a difference in those who persist at a motivational or locus of control level. For example, students with an external locus of control may get discouraged, as they cannot control an instructor or weather postponing their flight, in turn leading to a lack of motivation to continue (Dille & Mezack, 1991). Based on the findings, it may be beneficial for flight programs to attempt to limit instructor changes when possible or put programs in place designed to create effective matches between instructors and students.

A positive relationship was found between Maintenance Postponements and Time to Graduate. For every ten additional maintenance-related postponements per semester, on average, Time to Graduate increases by one semester. A possible explanation for this finding could be that, depending on the type of maintenance, a certain plane may be out of commission for a long period of time, leading to fewer options in the fleet for all students to choose from. This could lead to students' slow progress in flight classes and, therefore, delay the time to graduation. Moreover, Maintenance postponements are completely out of the students' control and may not only put them behind but may also discourage them in their progress.

No significant relationship was found between Student Postponements and Persistence Before Dropout; however, there may be practically significant findings. No relationship was found between Instructor Postponements and Time to Graduate. This may be due to the fact that those who graduate are very intrinsically motivated and are not affected by instructors postponing. No relationship was found between Student Postponements per semester and Time to Graduate; Weather Postponements and Time to Graduate; Maintenance postponements per semester and persistence; or Other Postponements and the two dependent variables. The lack of relationship between other postponements and the DVs may be due to the small number of "other" postponements (i.e., a small sample size). Additionally, the fact that the rest of the postponement variables may have covered the aspects that more commonly affect students. Furthermore, anecdotal reports by instructors support that students tend to. Based on the above findings, it might be beneficial for flight schools to put programs in place to cope with postponements. Students who begin acquiring large numbers of postponements should be made aware of potential impacts and provided assistance for making up lost ground and avoiding future delays.

Limitations, Delimitations, and Future Research

These findings should be interpreted with caution given several limitations of the study. First, we were not able to control how any of the data was collected by the university. This led to missing data. For example, both socioeconomic status and cognitive ability were removed from the analysis as there was too much missing data (i.e., 30% of the data were missing). This data may have added more insight. However, excluding variables in which 30% of the data is missing aides in unbiased results (Cohen et al., 2003). Future archival research should try to include an alternative, reliable and valid measure to capture any missing data of this kind. Furthermore, due to the recency of the creation of the Aviation Human Factors major, and lower enrollment in Aviation Meteorology, we were not able to include all flight majors. Therefore, future research should include students from other flight majors such as aviation human factors and meteorology. Future studies should attempt to replicate the study in different universities while collecting data related to student ethnicity to obtain a better understanding of the potential influences of international student pressures. Additionally, since we were using archival data, we were not able to collect all of the data we would have ideally used, such as information regarding student scholarships and grants, which could help augment the flight cost information. Future studies should also attempt to collect additional data, such as personality, motivation, locus of control, ethnicity, and scholarships. Finally, the sample data collected for the current study was a non-probability-based convenience sampling strategy, as all the archival data which was available from 2010 - 2016 was obtained from a single private university limiting the generalizability of the results. Future research should include data from more flight schools.

Conclusion

The current study established a prediction model with six sets of predictor variables and two dependent variables which were Time to Graduation and Persistence Before Dropout among pilot-in-training students in a Southeastern college in the U.S. The results indicate that Age, Number of Transfer Credit, Class Loads, and Pass Rates in Aero Classes are significant predictors of Time to Graduation and Persistence Before Dropout. In addition to that, Major Code, Academic Success in Aero Classes, and Maintenance Postponements are significant predictors of Time to Graduation. High Flight Costs, Instructor Changes, Student Postponements, and Weather Postponements are significant predictors of Persistence Before Dropout. We recommend older students – make aware of the program requirements and time expenditure. Class load – Students should be encouraged to take between 12 and 15 credits. Transfer students - may require more oversight or help to graduate on time. Postponements – Minimize postponements; make students aware of potential impacts and provide assistance in making up lost ground. Instructor Changes – Programs should attempt to limit instructors' changes.

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