Unveiling the Story Behind Numbers: Using Institutional Data to Reform Program Support for Online Graduate Students

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Abstract: A comparative longitudinal data analysis between two online non-thesis master's programs--natural resource management and environmental science--in a college of natural resources to determine the relationship between student characteristics and disenrollment risks. Risks varied between the two programs, with significance found to increase the risk of disenrollment due to cumulative GPA, gender, time between degrees, and the number of terms not enrolled.

Keywords: attrition, graduate online, environmental science, master of natural resource

This study evaluated longitudinal data from students enrolled in online master's non-thesis natural resource management and environmental science programs to develop a predictive model of disenrollment risk. The Cox proportional hazards model was used to analyze time as a factor of attrition behavior and identify student characteristics as predictors of attrition. Historically, attrition rates are routinely higher for both online and non-traditional students than their on-campus traditional student counterparts (Boston, et al., 2011; 2012; Coleman, 2019). As such, awareness of risk factors associated with student populations are essential to ensure appropriate support systems are in place to promote optimal student success.

The purpose of this research study was to determine if student characteristics, educational preparation, or institutional enrollment patterns can be used to predict student disenrollment for natural resource management and environmental sciences non-thesis master's programs with online options. The research questions for this study included: 1) does risk of disenrollment vary between the natural resource management and environmental science online graduate programs? 2) are there statistically significant relationships between student characteristics (gender, race/ethnicity, age, previous GPA, undergraduate degree field, time between degrees) and disenrollment risk by program? 3) do institutional behaviors (cumulative GPA, number of terms not enrolled) have a statistically significant relationship with disenrollment risk by program? In this paper we discuss supporting literature, research methodology for design, data collection, and analysis followed by results, discussion, and future research recommendations.

Literature Review

In many institutions, online graduate student populations are growing and constitute a large portion of graduate student populations, which has had a significant impact on institutional financial models (Cheslock & Jacuette, 2022). Online programs can be designed to accommodate part-time enrollment and asynchronous participation of learners who are unable to attend traditional campus programs or prefer the flexibility of an online platform. The structure of non-thesis graduate-level education can be appealing to working professionals with complex responsibilities or who live in remote locations. Despite differences between thesis and non-thesis programs, there are no standardized metrics for collecting data specific to master's non-thesis programs (Haydarov et al., 2013). Data from the National Center for Education Statistics (2012, 2020) showed postbaccalaureate online enrollments increased 10% between 2012 and 2020. One contributing factor to increased graduate enrollments is likely the expanded availability of online, non-thesis, course-based master's programs. However, the United States Department of Education does not delineate between non-thesis and thesis master's students. Ergo it is currently impossible to determine the level of enrollment increase or attrition of non-thesis students at the national level (National

Center for Educational Statistics, 2020). Analysis for attrition specific to non-thesis master's students must be conducted at the university or college level.

Rovai (2003) synthesized traditional models of student attrition and persistence developed for on-campus students into a composite persistence model for online non-traditional learners. Students come to distance learning and online graduate programs with different characteristics, skills, and challenges than students enrolled in traditional on-campus undergraduate and graduate programs (Rovai, 2003). The concept of student characteristics (age, ethnicity, gender, intellectual development, academic performance, academic preparation) and internal institutional factors were developed by Tinto for traditional on-campus undergraduate students (1975, 1982, 1997) and further developed for non-traditional on-campus students (Bean & Metzner, 1985). Bean and Metzner added elements to the internal institutional factors (e.g., study habits, advising, program fit, etc.) and external factors (finances, hours of employment, family responsibilities, life crises, etc.) that inform students' persistence decisions. Bean and Metzner removed social integration as an influence factor of persistence on the argument that non-traditional students have social networks outside the institution that influence persistence. In contrast, Workman and Stenard (1996) argued that social integration with peers and faculty for online non-traditional students was an influential factor on persistence, and Rovai agreed. Additional elements of the composite persistence model include student skills needed for success in an online educational environment such as computing and information literacy, time management (Rowantree, 1995).

The current literature pertaining to attrition and persistence in online graduate programs has focused on master's and doctoral programs in education and human social sciences (Coleman, 2019; Park & Choi, 2009; Park & Robinson, 2022), psychology (Kraiger et al., 2022), or nursing programs (Hayes Lane et al., 2022). Yet, there is a lack of literature specific to online programs in natural resource management or environmental sciences. To increase the understanding of this growing student population in natural resource management and environmental science (National Center for Education Statistics, 2012; 2022) this study focused on identifying student characteristics associated with attrition risk as a basis for evaluation of student support systems.

Rovai argued that increased "assessment, evaluation, and continuous improvement" is the "cornerstone of institutional effectiveness" (2009, p. 194). Other researchers have argued that measurement practices developed for undergraduate programs and traditional on-campus students are inappropriate for online graduate programs due to the increased complexity of mature adult learners who are frequently make up the bulk of online postbaccalaureate enrollments (Haydarov et al., 2013). Responsible evaluation of online graduate programs requires objective practices that accurately identify factors of attrition risk specific to non-traditional adult learners. Given limited understanding about students in non-thesis master's programs in the natural resource management and environmental sciences, this study inquired if online non-thesis master's students in natural resource management or environmental science are influenced by the same factors of attrition as students in other online student populations.

Methodology

After receiving IRB approval, longitudinal data from 2017 – 2023 was obtained from institutional research at a rural public university in the Pacific Northwest. The study sample included data from 620 students who enrolled in graduate programs with online options at a public institution. The data set included measures of students' previous education, demographics, semester by semester enrollment patterns, and institutional academic achievement. Comparisons were made between two non-thesis master's programs designed for online students: the Master of Natural Resources (MNR) program and the Environmental Science Master of Science (ENVS) program. Each 30-credit program was designed for working professionals to obtain a master's degree.

Participants

Within the ENVS program (n = 233) the age range was 20-71, with a mean age of 32 (S.D. = 8.5), 60% of the students were female. The age range for the MNR program (n = 387) was 20 - 77, with a mean age of 32 (S.D. = 8.4), 45% of the students were female. Both programs were predominantly white (ENVS 77% and MNR 85%). In the sample 242 students had graduated (ENVS = 125, MNR = 187) and 66 were considered disenrolled (ENVS = 15, MNR = 51), and 51% were eligible to continue taking courses (ENVS = 93 and MNR = 149).

Measures

Dependent Variable

The dependent variable of disenrollment was defined as students who were ineligible to take classes (Haydarov et a., 2013) and who did not graduate with a degree. There were three states a student could occupy: disenrolled, active, or graduated. The dependent variable was coded dichotomously as a 1 if the student had disenrolled from the program, or 0 if the student was eligible to register or had graduated from the program.

Independent Variables

Time was defined as length of time until the student experienced a target event (Coleman, 2019; Singer & Willette, 2003) and was measured in months. The beginning of time was the first day of the semester each student enrolled in the program. The end of time was measured as the end of spring 2023 semester. Individual demographic variables included gender, race/ethnicity, age, and military/veteran status (Rovai, 2009). Gender was measured as a binary. Race/Ethnicity was measured with dummy coding. Age was calculated at the time of first enrollment.

Education related experiences included if previous bachelor's was related to the natural resources, incoming GPA, and time between last degree (Rovai, 2009). Variables used to examine institutional education included stop-outs (terms with zero registration), credits per term, withdrawal, term GPA, cumulative GPA, disenrollment term, and graduation status. Graduation was measured at the institution level; students either graduated from ENVS or MNR or not at all.

Data Analyses

All data were analyzed with IBM SPSS Statistics (Version 29). Kaplan Meier (KM) is the simplest and most common method for comparing two populations over time, however KM cannot handle multiple covariates (Singer & Willett, 2003). Univariate KM models were used to look at the relationship between the outcome variable disenrollment and each predictor variable individually to determine significance of each predictor variable. The Cox proportional hazards model was used to create a predictive model of survival analysis to determine if students had graduated or disenrolled in relation to multiple predictor variables (2003). The hazard function was used to assess the risk of a disenrollment event and the survivor function was used to predict if students would persist to graduation.

Results

Kaplan Meier

A series of univariate models with KM examined the relationship between the outcome variable, disenrollment, with each individual predictor variable. The statistically significant education preparation predictor variables for ENVS included undergraduate GPA [$\chi2(3) = 7.894$, $p = .048$] and days between most recent degree for both programs (ENVS [$\chi2(119) = 168.64$, $p = .002$]; MNR [$\chi2(160) = 451.13$, $p < .001$]. The statistically significant student characteristic variables were race for ENVS [$\chi2(1) = 5.103$, $p = .024$] and gender for the MNR, with males at a greater risk for disenrollment [$\chi2(1) = 5.123$, $p = .024$]. Institutional behavior variables that were statistically significant included cumulative GPA for both programs (ENVS [$\chi2(56) = 82.03$ $p = .013$]; MNR [$\chi2(79) = 220.67$ $p < .001$]. The number of stop-out terms was only significant for the MNR [$\chi2(8) = 18.94$, $p = .015$]. Neither age, nor undergraduate degree in the natural resources variables were significant for either program. There were no cases of disenrollment for military or financial aid need in the MNR, or military for ENVS. Due to zero cases of disenrollment, (zero risk for disenrollment), the military and financial aid variables were removed from the full model.

Cox Model

The risk predictors of disenrollment were different between the two programs. The full Cox regression model for each program was specified with all predictor variables: age of first enrollment, stop-out terms, cumulative GPA, gender, race dummy variable, time between most recent degree, natural resource undergraduate degree, and undergraduate GPA. Only the MNR full model showed significant improvement over the constant-only model [$\chi2$ (6, n = 387) = 28.549, p < .001] indicating significance for stop-out terms ($p = .002$), cumulative GPA ($p < .001$), and time between most recent degree ($p = .021$). Holding with the KM, race alone was a significant predictor for ENVS disenrollment [$\chi2$ (1, n = 233) = 4.282, p < .039]. However, the significance of race was lost in the full Cox model with all predictors for ENVS.

Discussion

Research questions for this study included: 1) does risk of disenrollment vary between the natural resource management and environmental science online graduate programs? 2) are there statistically significant relationships between student characteristics (gender, race/ethnicity, age, previous GPA, undergraduate degree field, time between degrees) and disenrollment risk by program? 3) do institutional behaviors (cumulative GPA, number of terms not enrolled) have a statistically significant relationship with disenrollment risk by program?

The purpose of this research study was to extend research using student characteristics, academic preparation, and institutional behaviors to predict disenrollment in students enrolled in natural resources or environmental sciences non-thesis master's programs with online options. Study results suggest that disenrollment risk does vary between the ENVS and MNR programs. KM results indicate ENVS students with a race other than white may experience significant increase of risk of disenrollment (Li et al.,2022), while males were at a higher risk for disenrollment in the MNR. As such, support needed for each program to promote student persistence should be tailored to mitigate the specific risks.

Age did not influence disenrollment risk as found by Boston et al. (2011; 2012) and Park and Choi (2009). These results run contrary to other research where age was found to increase disenrollment risk (Coleman, 2019) or decrease disenrollment risk (Greene et al., 2015; Kizilcec & Halawa, 2015). Other student characteristics were not found to be statistically significant in relation to disenrollment risk despite previous research finding connections with financial need (Martinez-Carrascal et al., 2023), or military status (Boston et al., 2011; 2012).

Students without an undergraduate degree in natural resource fields or low undergraduate GPAs were not significant risk factors for disenrollment. Likewise, students from other disciplines pursuing either a natural resource management or environmental science non-thesis master's should not be construed as lack of academic preparation commonly associated with increase in disenrollment risk (Li et al., 2022; Martinez-Carrascal et al., 2023). Additionally, as time between the most recent degree and start of a master's program increases, so does the risk of disenrollment. However, other factors that may contribute to academic preparation such as work experience are not considered in this study.

Recommendations

The influence of transfer credits was not included in this study despite previous research findings indicating high influence on persistence (Boston et al., 2011; Boston et al., 2012). We recommend that institutions prioritize a practice of formalizing transfer credits upon admittance into programs rather than waiting to formalize with graduation applications. Additionally, gender is limited to male or female and does not reflect experience or potential disenrollment hazards to members of the LGBTQ+ community. We recommend that institutions implement changes to allow for more expression of gender identities. Additional recommendations for future research include expanding information on student soft skills such as literacy in discussion, reading, and writing (Rowantree, 1996). Furthermore, we recommend investigating the relationship between academic preparedness and work experience as work experience often bolsters soft skills. Finally, enrollment patterns and graduate course preparedness should be evaluated to determine behavioral changes pre and post onset of the COVID-19 pandemic.

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