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Utilizing Institutional Data for Curriculum Enhancement to Improve Student Success in Undergraduate Computing Programs

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UTILIZING INSTITUTIONAL DATA FOR CURRICULUM ENHANCEMENT TO IMPROVE STUDENT SUCCESS IN UNDERGRADUATE COMPUTING PROGRAMS

by

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ABSTRACT

Student success is one of the widely discussed topics in post-secondary institutions and is measured in terms of the graduation and retention rates of programs. The goal of an educational institution is to achieve maximum student success and, hence, high graduation and retention rates. There are multiple studies on factors affecting student success. One of the factors that contributes to student success is the "program curriculum." Unfortunately, the traditional program curricula at many higher education institutions were developed with a belief or assumption that all students possess equal expertise, skills, and follow a similar learning path. The traditional curricular development process neglects some specifics related to the characteristics of transfer and the First Time In College (FTIC) students and their time to graduation. The purpose of this research was to explore the relationship between the traditional program curricula and student degree mobility patterns to measure student success of transfer and FTIC students enrolled in Computer Science, Information Technology, and Computer Engineering undergraduate academic programs as well as how those relationships assist in the development and reform processes of curricula. This study was designed to understand the various aspects of program curricula, such as impacts of a program-specific factor, prerequisite, and post-requisite course requirements on time to graduation. This study leads to the development of Adaptive Curriculum Refinement, a novel approach based on institutional data analytics to assist higher education curriculum designers in the data-driven development of new curricula and data-driven revision of existing ones. The results of this study suggest a direct relationship between the curricular stringency and student time to graduation, whereas stringency was inversely related to the credit accumulation. The program-specific factor in the curriculum directly affects students' time to graduation. This study is significant because the results and the development of Adaptive Curriculum Refinement could inform higher education policymakers and assist curriculum designers about the need to reform program curricula based on a data-driven and evidence-based approach to improve student success.

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LIST OF ACRONYMS

ACT American College Testing

ACR Adaptive Curriculum Refinement

CE Computer Engineering

CS Computer Science

FTIC First Time In College

GPA Grade Point Average

IT Information Technology

RQ Research Question

SAT Scholastic Assessment Test

CHAPTER ONE: INTRODUCTION

Researchers from multiple areas such as psychology, social sciences, education, computing, etc. have been studying the phenomenon of undergraduate student success in postsecondary education over the years. The contemporary studies on student success began with the works of Tinto (1975, 2017) and Astin (1975). Since then, there have been many studies on student dropout characteristics, institutional policy reforms, student support programs, student engagement, student-focused curricula, etc. (Alexander, 2000; Chen, 2012; McCuddy, Pinar, & Gingerich, 2008; Trowler, 2010). In recent years, institutions have been using internally collected data to develop holistic models of student success to solve some of the significant challenges hindering students' retention and college completion. Thus, improving student success has become a major area of interest in many institutions. The goal to achieve high graduation and retention rates has become a key priority for postsecondary institutions.

Due to the demands of federal and state governments to improve the effectiveness and efficiency of higher education, many postsecondary institutions have started examining existing educational support programs and undertaking new initiatives to improve the graduation and retention rates of programs. However, the interest in improving student success metrics (time to graduation, graduation, and retention rates) varies from institution to institution.

Student Success and Persistence

The Input-Environment-Outcome model developed by Alexander Astin (1975) explains student success and persistence. Astin's model purported to examine (a) the preexisting characteristics of students before entering college, (b) the environmental factors of the institution, and (c) the impacts of college on students' life (Astin, 1991). Astin (1991) identified 146 possible factors related to students' preexisting characteristics before entering college and 192 environmental characteristics that might affect student success. These variables were grouped into eight groups: (a) institutional, (b) students' peer group, (c) faculty, (d) curriculum, (e) financial aid, (f) major field of choice, (g) place of residence, and (h) student involvement. The final component of Astin's model was the outcomes. Astin identified 82 outcomes, including student characteristics, knowledge, attitudes, beliefs, and values that exist after a student has graduated from college.

Vincent Tinto (1975) considered Astin's Input-Environment-Outcome model as a base model and built upon it to explain student persistence and success in the form of theory (Tinto, 1975, 2017). As per Tinto's (1975) theory, students enter college with a certain set of characteristics that either decrease or increase their commitment, dedication, and integration into the institution; the greater integration, which may be due to positive experiences, leads to higher retention, whereas lesser integration due to negative experiences results in lower retention. In other words, Tinto (2006) stated that institutional experiences contribute to students' persistence and success, which means students who were satisfied with their college experience graduate at a higher rate compared to those who were not.

Another theory of interest for academic advisors and higher education researchers is Holland's theory of vocational choice (Holland, 1959). Holland's (1959) theory helps explain the educational behaviors impacting student success. Holland (1959) emphasized educational and vocational behaviors are similar in terms of satisfaction, engagement, and stability in a field of study or within an educational institution. His theory emphasizes the sociological and psychological factors to understand educational satisfaction, stability, and achievement. Hence, these theories convey that multiple factors influence student persistence and success.

Course Grades, Program Curriculum, and Academic Success

Colleges and universities utilize a set of student characteristics and factors identified by Astin (1975), Tinto (1975, 1993) and others as predictors to determine which students are likely to succeed in college. The admissions department makes use of the Input-Environment-Outcome model, Tinto's (1975) model, and other models to select candidates and to track their degree progress. Also, institutions utilize students' pre-institutional factors such as Scholastic Aptitude Test (SAT) or American College Testing (ACT) scores and Grade Point Average (GPA) achieved at the previous college as a few predictors to decide which candidates to offer admission (Waugh, Micceri, & Takalkar, 1994). Once admitted, students' degree progress is measured by their GPA or grades obtained in courses. Even though there have been debates and discussions on whether to consider the GPAs as a predictor of student success, post-secondary institutions have been using GPA as the measure of students' academic success.

Innovative Applications to Improve Student Success

Colleges and universities have developed prediction models to improve student success with the help of enormous amounts of student data. Higher educational institutions have been using data mining and predictive analytic techniques to improve the success metrics of programs. However, most institutions have not taken advantage of large amounts of data to address issues that are inhibiting students' academic experience and success. More importantly, institutions have failed to leverage institutional data to develop a student-focused (or student-friendly) curriculum and personalized degree plans to enhance ongoing efforts to improve student success.

Due to the availability of advanced computing educational systems, institutions can take advantage of large datasets to develop new analytical techniques to predict and monitor academic success. The data managed internally by institutions play an important role in addressing various institutional challenges, including issues related to program curriculum. Institutional data are pivotal to understand the (a) underlying causes of institutional challenges hindering student success and (b) to take measures to reduce the effects of these challenges. Therefore, this study evaluated the usefulness of institutional data in designing the data-driven curriculum and predicting student outcomes.

<u>Home-grown Data Analytics and Off-the-Shelf Commercial Analytics Services</u>

Some higher education institutions have been using student information and personalized systems developed by private educational technology companies to monitor student progress in courses, degree, and other purposes (Blumenstyk, 2014). For example, Colorado State University has been using a system developed by the educational advisory board to assess students based on their chances of succeeding in a course using historical data. Even though the university spends millions of dollars to use these systems, the campus officials were not satisfied. There is a need to implement internal data analytic efforts within the institution to address challenges specific to student success. Many higher education institutions differ in scale and type of students they serve. For example, CS, IT, and CE programs considered in this study at the targeted university has a high percentage of transfer students. The commercial analytic systems were designed based on the standard features among all higher education institutions. These systems may fail to address some specific institutional factors such as curriculum assessment. Thus, the researcher urges institutions to increase in-house data analytic efforts to address issues specific to their academic programs and institution.

Purpose of the Study

The purpose of this study was to (a) determine if traditional (or current-in-practice) curriculum is helping or hindering student flow in the program towards their degree completion and (ii) develop a data-driven curriculum to address the issues of traditional curriculum. Based on the methodology of Adaptive Curriculum Refinement proposed in this study and resulting analyses, recommendations related to curriculum improvement and reform are provided.

Research Questions Specified

The following Research Questions (RQ) provided the focus for this study:

- RQ1: How does a traditional program curriculum impact students' degree mobility in the program and their success?
- RQ2: What are the drawbacks of a traditional program curriculum in achieving maximum student success from the researcher's perspective based on facts supported by data?
- RQ3: What drawbacks of the traditional curriculum (from RQ2) can be solved by using a data-driven approach for curriculum development and reform?

Significance of This Study

Higher education institutions use the graduation and retention rates of programs as an indication of their productivity and quality to attract prospective students, etc. In other words, students prefer (or choose) to enroll in institutions with satisfactory graduation and retention rates. Institutions have been implementing high impact practices and innovative techniques to improve the graduation and retention rates of programs. Despite the use of these metrics as an indicator for institutional improvement, the college completion rates nationally are significantly low. In other words, more students leave their program or drop out of college without getting a degree (Tinto, 1993).

Even though there has been extensive research in improving student success, the graduation rates have remained at 60% nationally (National Center for Education Statistics [NCES], 2018). At one of the largest public universities in the United States, the first-year retention and six-year graduation rates are 90% and 70%, respectively (University of Central Florida, 2020). Institutions have been coming up with new strategic plans to improve these metrics. However, there is a need to determine and address hidden institutional challenges and reduce the impact of these on students' college completion. More often, students leave the college when adversity strikes, but it is the responsibility of the institution to try retaining and guide them towards college completion. There are several reasons why examining challenges related to college success metrics is important and its benefits to students and institutions.

Institutional Goals and Commitments to Achieve Student Success

One of the major challenges in higher education institutions is to tackle issues related to curriculum, teaching, and advising to improve student success. One of the main goals of higher education institutions is to retain and graduate students. The graduation and retention rates of programs are major indicators of institutional quality and the commitment to provide quality education. Many institutions have been using these metrics to demonstrate their achievements to impact public perception, attract prospective students, and to increase institutional reputation. According to Bean (1986), student attrition is ordinarily viewed as student failure, but high rates of attrition represent institutional failure to retain and graduate students. Also, the attrition rates contribute to faculty interest in teaching to some extent. That is, when faculty teach at an institution with high attrition rates, then they are likely to feel negative towards themselves and their profession (Bean, 1986). These inferences support the need for institutions to conduct and expand research on student retention and graduation.

To achieve student success, institutions have begun implementing key strategies and action plans to address challenges that are inhibiting student college completion. Some of the action plans include starting a new student success program, evaluating existing programs, investing in programs that promote student success, etc. Besides, institutions need to consistently address challenges related to student success to improve college success metrics constantly. Thus, institutions must share lessons and experiences with other partner institutions to help them address similar issues.

Benefits of Higher Education for Students

Higher education plays an important role in the lives of students. One of the main goals of education is to help an individual develop, construct knowledge, and the ability to examine issues on all levels to solve them. Higher education helps to find a clear career path and plays a major role in promoting lifelong learning. Life is unpredictable, and no success story is without some level of challenge. Higher education teaches students how to learn, manage time, deal with the pressure and stress, and reach their goals. Apart from these, higher education helps improve the quality of life. Higher education also helps reduce unemployment rates and over-reliance on public assistance programs and contributes to improved economic growth (Baum & Payea, 2004). In general, college graduates will earn a yearly average of 1.74 times the amount of someone with a high school diploma (Ma, Pender, & Welch, 2019). This research expands traditional retention and academic success studies by introducing a data-driven approach for curriculum development.

Definition of Terms

Curricular analytics utilizing network science concepts

Curricular analytics is a framework that makes use of network science concepts and analytics to assess and compare existing program curricula across academic programs. This provides a means for predicting a likely impact of curricular reform within a particular academic program (Heileman, Abdallah, Slim, & Hickman, 2018).

Dropped out

The researcher referred students who left the target university without completing their major as students who “dropped out”. A percentage of these students may have “dropped out” of one institution only to continue their education in another one. We do not follow students across institutions. This study considered only institutional level data.

First-Time-in-College Students (FTIC)

"A student who has never attended a post-secondary college or university or who has attended an institution and earned less than twelve (12) semester credit hours of academic credit after high school graduation" (State University System of Florida, 2019, para. 1).

Program-Specific Factor

Some academic programs have program-specific factors such as a qualifying exam, exit exam, or graduation exams as a major requirement in the program curricula to test students' knowledge in the program's core concepts (or areas).

Program Plan of Study

Some academic programs recommend undergraduate students to take courses in a specific sequence to help them graduate on time. A program plan of study referred to as a roadmap to help students graduate (Elon University, n.d.).

Student Degree Mobility Within the Institution

How students' progress in their college journey either by staying in the same program or transitioning to other programs until they graduate or drop out of college.

Time to Graduation

The number of terms taken by a student to graduate from the time he or she first enrolled in their academic program.

Traditional Program Curriculum

A set of courses (with well-defined prerequisite requirements) that students required to take to graduate. The traditional program curriculum was developed based on experiences and ideas (experience-based and idea-driven) opposed to evidence-based and data-driven approach (Raji, Duggan, DeCotes, Huang, & Vander Zanden, 2018).

Transfer Student

Any student who has completed at least one hour of college credit in either a two- or four-year college after graduating high school (North Carolina Central University, 2018). The state of Florida guarantees students to earn a bachelor's degree in any state university college within Florida after they complete an Associate of Arts (AA) degree at a Florida college (Valencia College, n.d.).

Researcher's Experience and Stance

My interest in this topic comes from my personal experiences. Some of my struggles during my undergraduate and master's studies can be attributable to the following issues: (a) less clarity in what major to choose, (b) no proper guidance on selecting a set of classes and less friendly curriculum in terms of course offerings and subject interests, (c) limited availability of academic advising assistance, and (d) unclear about life after school (corporate job or graduate studies). Drawing from my own experience, I sought to understand how computing degree program curriculum are designed and developed and the underlying principle behind such development. In my role as a student researcher, I have been working on understanding the program curricula, incorporating data-based decision making in developing and reforming computing curriculum. I consider myself a reflective practitioner. This study considers a reflective practice's "learning from experiences" approach to construct meaning from my experiences. I believe this study will help to curb some of the issues I had faced during my studies so other students in the coming years do not have to face it while they are in college.

Assumptions and Possible Limitations

This study focuses on the effects of traditional program curriculum on undergraduate students' college completion. This study is based on a few assumptions: First, the students were intrinsically motivated to complete their undergraduate degree. Second, students were financially responsible for completing their degrees on time. Third, the researcher assumed the college has little or no resistance from its faculty members and administrative staff to implement student-centered measures and data-driven recommendations to improve student success. Fourth, this study assumed to reduce the time to graduation for students who wanted to graduate in their first program choice. At last, the researcher assumed that academic programs considered in this study were all equal in terms of quality and significance and are treated equally by administrators and faculty.

Some of the limitations of this study include that the data used in this study are from three computing programs in a large public university. The results of this study may apply to the only university under consideration due to the differences in nature and organization of programs within other institutions. However, the "Adaptive Curriculum Refinement" approach proposed in this study may assist other institutions for curriculum improvement and reform purposes. Finally, this study may not apply for new academic programs in their development stage. Since these programs do not have historical data; however, data from similar programs could serve as guidance.

Statement of Contributions

This dissertation made significant contributions to student success literature. Primarily, the Adaptive Curriculum Refinement is a new data-driven algorithm for curriculum evaluation and reform at a program level through which higher education institutions can improve their students' time to graduation. This new approach to evaluate curriculum uses student degree mobility patterns and network analytics. Also, this study provides a unique and novel way to analyze some of the drawbacks of program curriculum. Finally, this study introduced three new data-driven curriculum evaluation metrics: curriculum stringency, risk factor, and student mobility turbulence, which can be used by administrators, faculty, or curriculum designers to evaluate their existing program curriculum.

CHAPTER TWO: LITERATURE REVIEW

The ability to develop high-impact strategies to boost retention and graduation rates within higher education has been a focus of study in many institutional research and innovation centers (Burke, Parnell, Wesaw, & Kruger, 2017; Ekowo & Palmer, 2016). Despite the multiple studies, institutional practices based on educational research are frequently limited to the selective processes within the institution. As graduation and retention rates signify the quality of undergraduate education, institutions are under mounting pressure to develop strategic action plans to improve student success.

This literature review provides an overview of institutional challenges, factors, and trends that influence student retention and graduation. Specifically, a review of theories on retention and graduation and an overview of pre-college and institutional factors that influence student success are offered. The final section of this chapter provides the current institutional practice of following the state-of-the-art curriculum and associated research within higher education.

Student Retention and Student Success

Retaining students has been a primary focus for degree-granting institutions since the 1960s (Astin, 1975; Tinto, 1975). Institutions have been using prediction formulas or models for the admission process. Lately, predictions were made based on high school grade point average and standardized test scores of students (Burton & Ramist, 2002; Cohn, Cohn, Balch, & Bradley Jr, 2004). However, due to the complexity of retention phenomena and student success in general, predictions and mathematical models based on pre-institutional factors provided a foundation for extending the research on developing predictive models for student success.

Tinto (1975, 2017) and Astin(1975) identified numerous individual and institutional characteristics that predict student academic performance and success within higher education.

This study makes use of Tinto's (1975, 2017), Astin's (1975), and Holland's (1959) theories as a theoretical framework. The subsequent section reviews Tinto's Theory of Student Departure, Astin's Theory of Student Involvement, and Holland's Theory of Vocational Choice, which are three major theories that have contributed significantly to research on student retention and success.

Tinto's Theory of Student Departure

Tinto's theory of student departure is one of the most widely accepted theories in higher education research (Aljohani, 2016; Burke, 2019). This theory was developed by Vincent Tinto in 1975 and argued that academic (or institutional) and social experiences decide students' decision to stay in the college. According to Tinto (1993), students' college completion is dependent on their (a) personal and family experiences, (b) academic characteristics, and (c) institutional experiences gained during the college. Students enter higher education with a collection of their personal, family, and academic experiences, and this set of experiences decides students' initial commitment to the institution and their educational goals. With this initial commitment, students' interaction with the academic environment over time decides students' willingness to stay in the college. Positive interactions lead to greater integration and increased commitment to students' goals and educational commitments, whereas negative experiences lead to decreased commitment or disengagement to their educational goals. If disengagement continues, eventually, the student will leave college. Thus, student persistence is dependent on positive social and academic experiences. Tinto considered student interaction with faculty and peers as social integration, and grade performance and knowledge constructivism as academic integration. Lohfink and Paulsen (2005) have used Tinto's (1993) model as one of the theories to inform their study on comparing the determinants of persistence for first generation and continuing generation students at four-year institutions.

Tinto's Conceptual Model of Student Institutional Persistence

According to Tinto (2017), students seek to persist as opposed to being retained. Institutional interests are different from student interests. This model views student institutional persistence from student perspective. Student persistence cannot be achieved without the students' motivation. In higher education settings, there are multiple factors, including student experiences that decide their decision to persist or not. More often, student experiences gained during their time in college either enhance or diminish their motivation and hence their decision to graduate or not.

The experiences students gain during their college impacts their motivation and decision to persist. This overall phenomenon of student institutional persistence can be understood as the consequence of the interaction among student goals, self-efficacy, sense of belonging, and the value and relevance of the curriculum from a student perspective (Tinto, 2017). As per this model, students necessitated to have at least a goal to complete college. However, having the goal to complete college is not a sufficient condition because of the following reasons: (a) goals may vary by type and intensity as students' progress in their degree program, and; (b) college experiences often influence student goals and motivation. Due to these reasons, this model assumes that students enroll in college with some commitment to complete college and tried to understand the effects of college experiences on students' self-efficacy, sense of belonging, and perceptions of the value of curriculum.

Self-efficacy plays a vital role in student persistence. According to Bandura (1977), self-efficacy is a person's confidence in their ability to complete a task successfully. Some students possess a strong sense of self-efficacy, whereas other students have low self-efficacy. This may be due to the result of negative stereotypes others hold on some students or groups (Steele, 1997). Student self-efficacy is more important than their academic ability to take an enormous responsibility of completing college (Tinto, 2017). In addition to self-efficacy, students' sense of belonging in the campus environment plays an important role in persistence and college completion. The feeling of belonging was decided by student interaction with the campus community members such as other students, faculty, staff, and administrators (Hurtado & Ponjuan, 2005). Students who perceived themselves as belonging on campus tend to persist at a higher rate (Hausmann, Schofield, & Woods, 2007).

Students' perception of the curriculum in terms of its value and relevance to subjects that concern them influence their motivation to persist (Tessema, Ready, & Yu, 2012). Students' perception of the curriculum provides a sense of idea on other institutional issues such as faculty teaching methods, institutional quality, and student learning preferences and values (Zepke, 2015). More importantly, students need to feel that what they are learning from the courses in the curriculum is of sufficient quality (Frick, Chadha, Watson, Wang, & Green, 2009). Thus, higher education institutions must develop institutional policies and programs that are student-friendly to improve student persistence.

Astin's Theory of Student Involvement

Alexander Astin is one of the famous educational theorists, and his work on student retention has been serving as one of the base models for higher education researchers (Astin, 1975). Astin emphasized student interactions with their peers and faculty as the means to improve retention. Like Tinto's model, Astin's model also emphasizes academic and social aspects of college as the requirement for college retention. When students are involved more in the academic and social aspects of college, then they learn more and vice versa. Student involvement is measured by the considerable amount of time spent on academics, extracurricular activities, interaction with peers, and interaction with faculty (Astin, 1993).

Frequent and high-quality interactions in academic activities influence students' learning and development (Astin, 1975). Astin found that frequent interactions with faculty are strongly correlated with college satisfaction and academic activities. The active participation of students is necessary to improve their academic performance and retention (Astin, 1984). Student goals, interests, and commitment decide students' involvement in higher education (Astin, 1984). Thus, Astin's theory emphasized students to be active participants in gaining and participating in the opportunities provided by the college. Astin also claimed students will become efficient learners when faculty, staff, and institutional administrators unify their efforts to promote student involvement (Astin, 1993). Astin's studies provide a basis for applications such as the curriculum design and reform and the delivery of course content and convey the importance of student involvement in achieving satisfactory retention and college completion rates.

Holland's Theory of Vocational Choice

John Holland is a famous psychologist, and his work on vocational choices explains how individuals make decisions regarding their careers; it is regarded as a base theory for career choice related studies (Leung, 2008). Holland (1977) stated that educational behaviors, such as choice, stability, satisfaction, and achievement resemble vocational behaviors. Though the actors in this theory are adults, many education researchers have accepted the fact that this theory holds good for higher education institutions in contributing to student success (Smart, Feldman, & Ethington, 2006). Two of three major assumptions of Holland's theory can serve as the basis for patterns of student success in higher education. First, students' choice of major is an expression of their personality. Most people fall under one of these six personality types: Realistic, Investigative, Artistic, Social, Enterprising, Conventional. According to Holland, students who prefer to major in computing (or technical) programs tend to be more of the investigative types (Smart, Feldman, & Ethington, 2006). However, they may fall under one of the other five types. Second, student success is a measure of how well students improve their abilities and interests that are reinforced and rewarded by their chosen program. Thus, the chosen program (or academic environment) plays a vital role and has a greater impact on student success.

Supportive academic environment that encourages students' involvement helps them to stay in the program. Students leave the program when they feel their program does not support their involvement and persistence and they start to find a different place (or program) within the university where they get the support they need (Reardon & Bullock, 2004). To decrease the program dropout and change of major rates, Reardon and Bullock (2004) used Holland's theory as theoretical support for their "service-delivery model" to assist students in program selection. Thus, Holland's theory is an applicable theory when studying student success in higher education.

Students' Pre-Institutional Factors Affecting Student Success

Some higher education institutions have been using a set of pre-institutional factors to select candidates who were most likely to succeed in the college (Cohn et al., 2004). Institutions have been utilizing admission formulas and predictive models that include standardized test scores and high school grade point average as the basis for selection.

Multiple studies in the literature show pre-institutional factors such as high school grade point average and standardized test scores to be good predictors of academic success (Burton & Ramist, 2002; McDowell, 1995; Thompson, 1998). Morrison and Schmit (2010) have shown that the American College Test (ACT) math score and high-school GPA are directly related to student success in course completion at the North Iowa Area Community College. Mau (2016) tracked college students over five years and identified factors that influence persistence. Students' ACT scores and high school GPA significantly predicted student persistence. Factors such as students' ACT scores, high school GPA, institution, type of students, first-year GPA, and cumulative credits earned decided students' likelihood of declaring as a computing major (Mau, 2016).

Similarly, Giannako, Pappas, Jaccheri, and Sampson (2017) carried out a study at the Norwegian University of Science and Technology to determine positive factors that decide retention of students in the computer science department. Factors such as degree usefulness, cognitive gains, and supportive environment increase student retention, whereas negative feelings reduce student retention. In addition to these studies, a study by Zhuhadar, Daday, Marklin, Kessler, and Helbig (2017) found that a majority of students in mathematics program tend to drop in their second year and those who have been long overdue to finish college have a higher tendency of dropping out.

Prior course experience is another factor studied as a student success indicator. Katz, Allbritton, Aronis, Wilson, and Soffa (2006) studied the reasons behind promising students leaving the CS pipeline. The verbal SAT score, the number of calculus courses taken, prior computing experience, access to a computer at home and the existence of a motivational role model during high school are shown to be indicators of both performance and persistence of students in undergraduate CS programs.

The curriculum structure, course sequence, and syllabus are also shown to affect student success. Adams, Pérez, and Ballard (2007) created a program to increase the enrollment of transfer students at the Lincoln College of Engineering, University of Nebraska. The program lets students complete some basic level courses while they were at the community college before being transferred to the University of Nebraska. In a similar project, Anderson-Rowland (2006) aimed to retain transfer students in engineering and computer science majors. The project directed thesis students to attend graduate school right after the completion or after a few years of completion of the major and showed considerable success. Thus, pre-institutional variables such as standardized test scores, high school academic performance, and courses taken during high school act as a tool for screening new applicants in higher education.

Institutional Factors Affecting Student Success

Xu, Xing, and van der Schaar (2016) analyzed student survey data about the college experience of computing programs at the University of Memphis. The data analysis showed that the academic quality provided by the institution, academic integration, and student motivation for active learning have shown to be the most influential retention factors (Xu et al., 2016). Surprisingly, financial pressure and accessibility to instructors outside the classroom are not correlated with student retention. Xu et al. (2016) emphasized that higher education administration should include an emphasis on improving teaching skills of faculty, reduced class sizes, actively engaging students in research projects, and promoting active learning.

A study by Dika and D'Amico (2016) focused on factors that influence the persistence of first-generation STEM students. Factors such as math preparation and perceived social fit were found to influence success. In a similar study, removing institutional barriers and undertaking interventions that improve students' motivation, interest, and ability to persist in computing programs help underrepresented students stay in college and complete (Estrada, Burnett, Campbell, Campbell, Denetclaw, Gutiérrez, & Okpodu, 2016). Promoting active learning and addressing student resource disparities has a positive impact on underrepresented student success. The undergraduate research experience has also shown to increase self-efficacy and career ambitions for students in computing programs (Carpi, Ronan, Falconer, & Lents, 2017).

Financial aid is one of the factors that decide student success (Olbrecht, Romano, and Teigen, 2016). The financial state of students' family, whether a student is getting financial help from family or not, also influence student success. Olbrecht et al. (2016) found that if a student's family supports him or her by covering the student's educational costs, then that improves the student's chance of retaining in college. Also, financial assistance provided by the institution strengthens students' likelihood of continuing in college (Olbrecht et al., 2016).

Even though the studies mentioned above are valid for all types of students, transfer student success is often influenced by additional factors.

Transfer Student Characteristics

Multiple factors influence the retention and college completion of transfer students in two- and four- year institutions (Baker, 2016). For instance, their previous college experience, father's highest education level, earning associate degree, transfer GPA, transfer credit hours, and courses passed at a community college are indicators of transfer students' college completion (Lopez & Jones, 2017). Unlike freshmen, transfer students have to navigate the academic environments in regard to satisfy the transfer requirements of the four-year institution, while they are in two-year or community college.

Transfer students often face challenged to adjust to their new academic institution after graduating from two-year colleges. Transfer student persistence is crucial for institutions to improve their graduation rates. Higher education institutions have started student support services to assist transfer students to improve their persistence. Dennis et al. (2008) emphasized the importance of considering students' characteristics and their GPA while creating support services for transfer students. In addition, studies have shown the importance of individual factors such as student motivation, self-efficacy, and commitment to college, as well as institutional factors such as academic rigor, and the quality of advising on college completion (Kirk-Kuwaye & Kirk-Kuwaye, 2007; Laanan, Starobin, & Eggleston, 2010).

Overall, retention and college completion rates of transfer students are affected by multiple factors. Institutions attempt to improve transfer student retention and completion rates by implementing innovative interventions, such as one-on-one advising for finalizing course plans (Bettinger & Baker, 2014). Other interventions include career workshops and mandatory transfer orientations (Derby & Smith, 2004; Zeidenberg, Jenkins, & Calcagno, 2007).

To make the transfer process smooth and help students to get a degree in four-year institutions, many local community colleges have agreements with four-year institutions.

Articulation Agreements

Articulation agreements are formal partnerships between some community colleges (or two-year institutions) and four-year institutions (Barrington, 2020). Even though all community colleges help their students to transfer to four-year colleges and universities, only some community colleges guarantee admission to four-year postsecondary institutions. As per Kamen et al. (2019) and Barrington (2020), the articulation agreement is a signed legal contract which pays significant attention to policies related to admission guarantees, credit transfers, transfer program comparisons between two-year and four-year institutions, and transfer scholarships. Each state in the United States have a different transfer policy standard for students who want to transfer to four-year colleges and universities. For example, in case of Florida state college system, community college students who complete an associate degree can transfer to four-year colleges or universities (Barrington, 2020). Also, students can request Associate of Arts (AA) certificates if they complete minimum requirements for the degree, whereas students in Georgia do not have this option (Transfer and Articulation: All State Profiles, 2020). Shapiro et al. (2017) study has shown that having an articulation agreement between community colleges and four-year institutions helps to improve the enrollment rates at the four-year institution.

Role of Faculty/Mentor and Academic Assistance in Student Success

Higher education institutions can be viewed as the knowledge construction and exchange venue where students interact, learn, and exchange information with faculty. Studies have shown that having a caring faculty mentor helps in achieving maximum student engagement (Soria & Stebleton, 2012; Tinto, 2006). Student engagement is one of the drivers contributing to student success, and faculty and staff play an important role in achieving it. Students who perceive that they have a good connection with a faculty or mentor in their academics were more successful (Clark, Walker, & Keith, 2002; Grosset, 1993; Jackson, Smith, & Hill, 2003).

In addition to the roles of faculty and mentor, academic assistance and undergraduate support programs play a vital role in student success. Students who have positive impressions of the support they get from the department are more likely to succeed than those who did not (Brooks & DuBois, 1995). Also, students who participate in small group support sessions and one-on-one training sessions had better academic performance than their counterparts (Folger, Carter, & Chase, 2004).

Applications of Predictive Analytics in Higher Education

Higher educational institutions have been using data mining and predictive analytics techniques to increase graduation and retention rates of their programs (Neelakantan, 2019). The institutions use these techniques to improve the resource allocation and utilization of their programs. For instance, Basavaraj, Sedghi, Garibay, Ozmen, & Guha, (2020) analyzed institutional level data to improve the success rate of computer science qualifying test. With the help of the data analysis, the Computer Science (CS) department at the University of Central Florida changed the program resource allocation and the structure of the qualifying test. These changes positively impacted the success rate of the qualifying test and consequently the graduation rate of CS program (Basavaraj et al., 2020).

The president of Georgia State University (GSU), Mark Becker initiated the use of big data at GSU to improve academic and career success rates (Ekowo & Palmer, 2016). GSU used predictive analytics to determine which students were likely to graduate by analyzing two and half million grades earned by students over ten years. Also, this big data has been used to support student advising, manage staff effectively and to make strategic management decisions at GSU and other universities.

There are institutions that use course-level data to forecast student graduation. For example, Arnold and Pistilli (2012) used data and predictive analytics to forecast student success algorithm at the Purdue University. They used course management data to predict whether a student will succeed in a course or not. This technique helped many students in successful course completion by notifying them whenever care must be taken to improve their grades.

In addition to these universities mentioned above, there are many other institutions in the United States which have been using innovative applications like predictive analytics and data mining techniques to solve institutional challenges and to improve students' success.

Curriculum Improvement in Higher Education

Most program curricula are planned and organized by academic staff (Stark, Lowther, Sharp, & Arnold, 1997; Briggs, 2007; Oliver & Hyun, 2011). While these staff may be experts in their field, they lack experience of what it is to be a student in the 21st century. In other words, traditional curricula were designed based on experiences gathered by the staff or faculty who oversaw the curriculum design process as opposed to data-driven pieces of evidence. For a curriculum to be effective, it must meet student needs and requirements (Boud & Dochy, 2010; Hubball & Gold, 2007). Two ways in which this can be achieved is by either including students during the curriculum design process or by a thorough analysis of students' performance data. A thorough analysis of data provides insights into what is working and not working for students. Incorporating these in the curriculum improvement at a program level helps to improve graduation rates and hence student success. Basavaraj et al. (2020) revised a CS program curriculum by analyzing institutional level data of five thousand students to improve graduation rates. Within two years, the graduation rates of CS program improved by ten percent.

Data-Driven Approach for Curriculum Improvement

Data-driven decision making has become pervasive in academic institutions (McKenzie, 2019). Specifically, the usage of data to identify the patterns of retention and graduation of students over the years has provided an instrument to propose and implement measures to improve student outcomes (Burke, Parnell, Wesaw, & Kruger, 2017). The data-driven processes allow university leaders, faculty members, and administrative staff to make accurate decisions related to students and university.

University leaders use college-level data to monitor progress and to identify areas of need. Also, they use data for policy development and planning (Schildkamp & Kuiper, 2010). Faculty members are interested in classroom-level data to monitor students' progress in courses they teach and to improve their teaching performance. Thus, different stakeholders are interested in using data to improve student success.

Even though there exists a huge amount of data within universities, still decisions are made based on personal experiences when it comes to improving student outcomes (Green, 2018). This may be due to the resistant nature of organizational leaders because of their limited knowledge and the cost of data-informed reforms within the institution. School leaders or higher authorities play a vital role in institutional decision making. Schildkamp and Kuiper (2010) argued that having a supportive school leader who promotes to use data to improve student outcomes is essential to data-driven decision making in curricular reform.

Curricular reform is one of the topics within higher education institutions that authorities and leadership committees have been skeptical and resistant about accepting data-informed decision making (Logue, 2018). Logue (2018) argued that faculty members and administrators were resistant to curricular reform due to it being hard to obtain resources required for improvement at the City University of New York. Among all these confusions, there is a decent amount of interest in the higher education community to include data-informed decision making to improve the curricular reform process and to develop data-driven curriculum. Wolf (2007) developed a model for curriculum development in higher education using educational developer support and perceptions from relevant stakeholders such as lecturers, alumni, graduating students, entering students, and employers. These studies signify that incorporating data into curricular development and reform is essential.

Curriculum Design Analysis Process

The common analytic process within organizations consists of five stages as follows (Norris & Baer, 2012): (a) initiate the process with a strategic question, (b) find or collect the appropriate data for the analysis, (c) analyze data to provide insights and make predictions, (d) convert the data in a way that is understandable and actionable, and (e) provide feedback in the process of addressing strategic question. However, in some cases, all stages need not be taken into consideration in the process. For example, sometimes data can be visualized directly without the need to be analyzed. Similarly, the curriculum design analysis process consists of five stages (Chang, Tsao, Kuo, & Hsu, 2016) as shown in Figure 1.

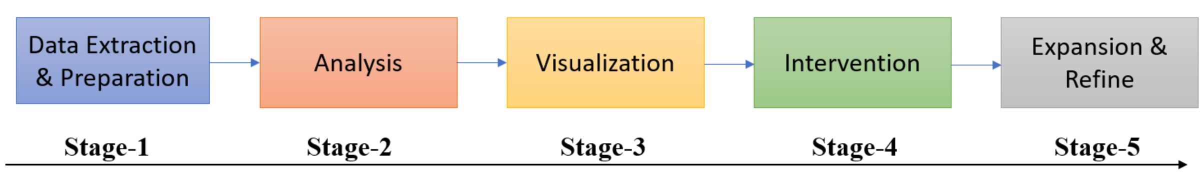


Figure 1: Curriculum analysis design process (adapted from (Chang, Tsao, Kuo, & Hsu, 2016)).

Stage-1: Data Extraction and Preparation

This stage consists of data extraction, data transformation, and data preparation stages. The data extraction consists of extracting data from data storage centers either by interfaces such as open database connectivity or file downloads. After extraction, data are transformed to have consistent data reference types, and data are prepared to answer strategic questions represented by correct statistics.

Stage-2: Data Analysis

After data preparation, data can be analyzed using inferential statistics, descriptive statistics, or data mining techniques. The structured data are reorganized and computed in this stage of the process.

Stage-3: Data Visualization

Data visualization is the most important stage for decision making in the curricular analytic process. This stage integrates human experience and knowledge with machine intelligence.

Stage-4: Interventions

Recommendations (or interventions) are provided based on descriptive statistics or predictive modeling. Proposing interventions require domain knowledge. The data analyses and visualizations are used by domain experts and researchers to implement actions for improvements.

Stage-5: Expansion and Refine

This stage is also referred to as a feedback stage, whereas Stages 1-4 are revisited to evaluate and verify the results.

Summary

This literature review provides a context for the study of utilizing institutional data to develop data-driven curriculum and to predict academic success. The institution's commitment to retain and graduate every student is a vital component for student success (Tinto, 2006).

The works of three major theorists were reviewed to provide a foundation for this study. Astin's (1975), Tinto's (1975, 2017) theories provide a theoretical framework regarding college completion phenomenon, and Holland's (1959) theory provides the reasoning behind student transitions within an institution. The literature provides a foundation for intervention strategies to improve the curriculum development and reform processes (Chang et al., 2016).

The literature provides a thorough review of factors affecting student persistence and success and provides insights into factors to consider while developing a data-driven curriculum and personalized course recommendations. Institutional factors such as the program curriculum, program quality, teaching skills of faculty, active learning, the availability of financial aid, academic assistance, and faculty concern for student academic growth affect student success (Akbaş, Basavaraj, & Georgiopoulos, 2015; Basavaraj & Garibay, 2019; Olbrecht et al., 2016; Xu et al., 2016). These factors help students to meet the academic demands of their respective programs. Also, students' experience with the department and institution influence their decision to stay in college and graduate.

"Course grades" provide a measure of whether students were able to adjust to the course and academic challenges (Cabrera, Nora, & Castañeda, 1993; Porter, 1990; Waugh et al., 1994). Low, fail, or withdrawn grades in courses indicate students' inability to face academic challenges and institutional failure to help them during their challenges. Similarly, studies have shown low-grade point average indicates students' response of not adjusting to the institutional environment and hence institutional failure to assist them in getting good grades (Bean, 1986).

In a review of previous data-driven curriculum literature, institutions have shown interest in using data to develop and reform program curriculum (Akbaş et al., 2015; Basavaraj et al., 2020; Wigdahl et al., 2014). Studies cited in this chapter have found that higher education administration and faculty were resistant and slower to adopt the data-informed changes to the program curriculum (Logue, 2018). Also, the review of curriculum analysis design process is provided to understand the process of the curricular analytic process to refine existing curriculum based on institutional data.

This study contributes to the existing literature by making use of institutional-level data to study and improve the traditional undergraduate program curriculum. Multiple studies have reported the impact of program curriculum on student success (Akbaş et al., 2015; Basavaraj & Garibay, 2018). However, few studies in the literature made use of institutional data to study the program curriculum, courses, and its impact on student success (Arnold & Pistilli, 2012; Asif, Merceron, Ali, & Haider, 2017; Gray & Perkins, 2019). These studies focused on either understanding the relationship between courses and the impact of course grades on students' degree completion or how course choices impact students' graduation. However, no study attempted to understand the program curriculum from a perspective of student mobility in their academic programs as well as between programs within the institution using internally managed data.

Few studies that have used analytical techniques to investigate the relationship between curricular metrics and student success (Carpenter, Dopson, Kim, & Kniatt, 2016; Heileman, Abdallah, Slim, & Hickman, 2018; Slim, Kozlick, Heileman, Wigdahl, & Abdallah, 2014). However, these studies have not taken the complete advantage of institution-level data to understand the relationships between the program curriculum structure and students' time to graduation. Specifically, these studies have not investigated the impact of a program-specific factor in the program curriculum, and the significance of corequisite requirements on student time to graduation.

This study bridged the gap between the use of institutional data and the curriculum assessment and reform processes at a program level by taking advantage of institutional data to understand the impact of program curriculum structure on student degree progression. Then the study determined some of the drawbacks of the traditional program curriculum and developed a system to reduce students' time to graduation. This study introduced two new metrics that take into account institutional level data to understand the relationships between the program curriculum structure and time to graduation.

The purpose of this study is to expand traditional student success literature by integrating the data-driven approach to either evaluate or reform program curriculum from institutional data.

CHAPTER THREE: RESEARCH METHODOLOGY

Research Design

This study followed a causal-comparative research design process and examined the relationship between variables related to program curricula and student degree mobility patterns that represent students' academic success. In addition, the researcher developed an algorithm to assist higher educational institutions in developing a data-driven curriculum or reforming the existing program curriculum.

Data

Data for this study consisted of a sample of students enrolled in Computer Science (CS), Information Technology (IT), and Computer Engineering (CE) undergraduate programs during fall 2013 semester. The sample consisted of 6,897 records representing 494 unique students of three computing programs at a large public university in the Southeast. A total of 253 transfer and 241 FTIC students comprised the sample. The transfer student population is slightly greater than that of FTIC students.

Usage of Additional Data for Computer Science Program

In addition to fall 2013 cohort data, institutional data of academic years 2004–2012 of the Computer Science program were used to study the effects of a program-specific factor in the program curriculum on the graduation rates. A total of 4,557 student records comprised a sample, which included both transfer and FTIC students.

Variables Used in This Study

Institutional Knowledge Management (IKM) at the target university routinely collect and maintain student data. This study utilized 15 variables provided by the institutional research office. Table 1 provides a brief description of the independent variables used in this study.

Table 1: Institutional Variables Used in This Study

Variable	Description
Academic program	Student's primary program.
Admission type	Student's primary admission type
Admit term	Term when students received admission offer for the term they applied
Program enrollment semester-wise	Term-wise program enrollments
Academic Load	Number of credit hours enrolled per Semester
Program start term	Term when students first enrolled in the program
Course Prefix and Number	The course prefix and course number of the course
Course Term	Term when students enrolled in a course or set of courses
Course Grade	The final course grade expressed in English alphabets (A, B, C, etc.)
Credit hours	Passed credit hours accumulated towards graduation
Degree Completion Term	Semester when the student completed the degree
Degree Awarded Program	Student degree program
Degree Awarded Semester	Semester when student completed the degree

Dependent Variables

The purpose of this study was to understand how traditional curriculum impacts student degree mobility within a four-year institution and to develop a framework for curricular reform to aid institutions in improving academic success. Student academic success was measured by their Grade Point Average (GPA), which is calculated by considering grades obtained in courses that count towards their degree program. This study considered both GPA and course grades as dependent variables (Cabrera et al., 1993; Porter, 1990).

Student academic success was assessed through three perspectives in this study. The first perspective was student GPA—those who graduate with a GPA greater than or equal to 2.5. The second perspective defined academic success as those who graduated irrespective of whether they changed their major or not. The last approach defined academic success as those who are still in the program with a GPA of 2.5 or above.

Data Preparation for Analysis

The data used in this study were provided by the university's institutional research office. The data consist of a total of eight tables comprising information related to students' term enrollment, cohort, course and degree data, and transfer information.

Data Filtering to Remove Irrelevant Records

Irrelevant data were removed from the overall dataset. Irrelevant data in this study were defined as records not corresponding to either transfer or the FTIC students and records with students having a graduate classification as defined in the academic level. In addition, records of students who were readmitted to the same program were not considered in this study to avoid redundancy and confusion. Some students had course records of CS, IT, or CE programs even before they enrolled in these programs for the first time. Some student records had two grade entries for the same course in the same term. These records were not considered in this study.

Calculated Variables

Some variables in the dataset were calculated to facilitate analyses. The calculated variables are shown in Table 2. In this study context, student success was defined as follows: graduating with a degree in any academic program within six years of admission.

Table 2: Calculated Variables Used in the Study

Calculated Variable	Description
Course Related Variables	*Calculated for all courses in the program curriculum.*
$\mathbf{Avg_{taken}}$	The average number of times a course had taken by a distinct user.
$\mathbf{Avg_{failed}}$	The average number of times failed by a distinct user in a course.
$\mathbf{Avg_{grade}}$	Average grade of a course.
$\mathbf{R_f}$	Risk factor of a course.
$\mathbf{DM_c}$	The difficulty metric of a course.
$\mathbf{Avg_{Rf}}$	The average of risk factors of all courses in the program curriculum.
Degree Related Variables	
$\mathbf{Avg_{timetograd}}$	Average time to graduation.
$\mathbf{DR_i}$	The number of students dropped out at the end of term *i*.
$\mathbf{CM_i}$	The number of students who changed their major at the end of i^{th} term.

Coding Independent Variables for Analysis

Some of the variables were coded for analyses. These variables are summarized in Table 3.

Table 3: Coded Independent Variables for Analysis

Variable	Coding	
Student Success	1: Graduated	
	0: Dropped Out	
	2: Changed Major	
Transfer Status	1: Transfer	
	0: First Time in College	
Course Grade	A	4.0
	A-	3.75
	B+	3.25
	B	3.00
	B-	2.75
	C+	2.20
	C	2.00
	C-	1.75
	D+	1.25
	D	1.00
	D-	.75
	F	0.00
	W	0.00
Academic Load	1: Full-time	
	0: Part-Time	
Qualifying Exam	Pass: 4.0	
	Fail: 0	
Grade	NC – No credit	

Research Question One

The study first determined if the traditional curriculum of three undergraduate programs affects students' degree mobility patterns and their time to degree. The two main components investigated were curricular analytics and student degree mobility patterns.

Curricular analytics utilizing network science concepts were used to analyze the degree of relationships between program curriculum and graduation metrics. One of the curricular analytic metrics, "curriculum rigidity," was used to determine how rigid the program curriculum was in terms of students progressing towards graduation (Wigdahl, Heileman, Slim, & Abdallah, 2014). In other words, the curriculum rigidity refers to the degree of the rigidness of the program curriculum in contributing to retention and college completion. In addition, a new metric, "curriculum stringency," was introduced in the study to consider the significance of historical data related to student performance (Basavaraj & Garibay, 2020). The curriculum stringency is defined as follows:

$$Curriculum\ Stringency = \begin{cases} \sum \mathrm{deg^o(v)}\ /\ |\mathrm{V}| + \mathrm{DM_{psf}}, & \text{if } \mathrm{DM_{psf}} \neq 0 \\ \sum deg^o(v)\ /\ |V|, & otherwise \end{cases} \tag{3.1}$$

$$DM_{\mathrm{psf}} = Avg_{\mathrm{taken}} * (Avg_{\mathrm{failed}} + 1)/Avg_{\mathrm{grade}} \tag{3.2}$$

Where $deg^o(v)$ represents the outdegree of each node in the program curriculum. DM_{psf} represents the difficulty metric of any program-specific factors such as qualifying exam, skill assessment exam, graduation or exit exams, etc. The difficulty metric considers the average number of times a student had taken the exam, the average number of times a student had failed, and the average grade of the exam.

The significance of curriculum stringency is to determine how difficult a program curricular structure concerning student degree progression. In other words, this metric gives an idea of how hard the curricular structure for a student to progress in their degree program. The curriculum hardness is either due to the presence of many prerequisites and post-requisite requirements or the presence of a program-specific factor. This metric can also be used to compare program curricular structures of two or more programs. For example, if the curriculum stringency of program-A is greater than program-B then program-A is difficult compared to program-B in terms of completing courses. This metric even considers the difficulty level of a program specific factor (e.g., qualifying exam) by considering students' past performance in the program-specific factor.

The difficulty metric measures the difficulty of a program-specific factor by considering the students' past performance data. This metric helps to understand how difficult the program-specific factor in contributing to student graduation. If the difficulty metric value of a program-specific factor is high, then it has a significant impact on students' graduation and time to degree.

Student degree mobility patterns were studied with the help of student flow visualizations (Morse, 2014), which were created using institutional data. The mechanism to create these diagrams is shown in Figure 2.

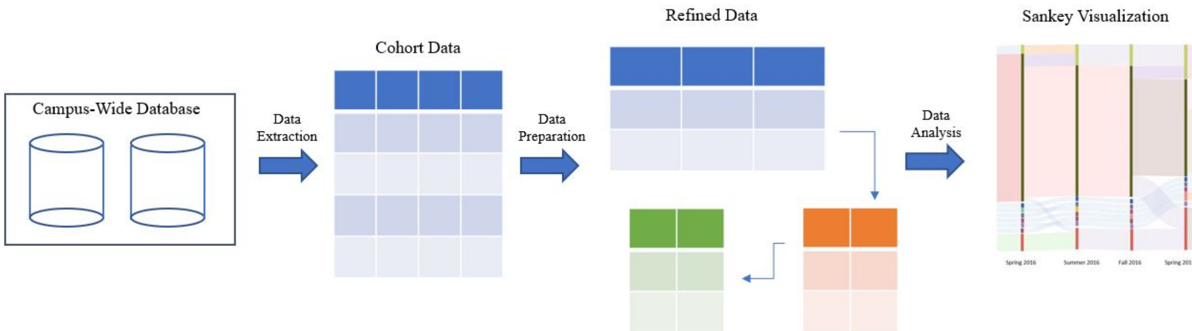


Figure 2: Mechanism to create student flow visualizations.

A metric 'Student Mobility Turbulence' was introduced in the study to measure structural complexity of student flow visualizations. This metric was deduced based on two important relationships among dropout rates, rate of change of majors, and the graduation rates: (a) dropout rates negatively affect graduation rates (Cook & Pullaro, 2010) and (b) graduation rates was not affected by students changing majors in the first three terms of their enrollment (Foraker, 2012). The student mobility turbulence measure is defined in Equation 3.3:

$$Student\ Mobility\ Turbulence = \frac{(c1\sum_{i=1}^{n} num(DR)_i + c2\ \sum_{i=3}^{n} num(CM)_j)}{N} \qquad (3.3)$$

Where *num* $(DR)_i$ represents the number of students who dropped out at the end of i^{th} term, and *num* $(CM)_j$ represents the number of students who changed their major at the end of j^{th} term. N denotes the total number of students who dropped out as well as those who changed their majors. *c1* and *c2* are coefficients.

Student mobility turbulence metric explains the degree of distortion of student degree mobility within the institution. In other words, student mobility turbulence explains whether students in the program under study are progressing in their degree at a satisfactory rate or not. For example, if a student mobility turbulence of program-A (based on student flow visualization) is greater than program-B, then program-A is more distorted in terms of student degree mobility. In other words, the change of major and dropping rates of students in program-A is greater than program-B. These kinds of comparisons can also be made for two or more student groups (e.g., transfer and FTIC students) in the same program with the help of mobility turbulence metric.

Research Question Two

As mentioned above, the program curriculum is one of the institutional factors affecting student success (Kuh, Kinzie, Schuh, & Whitt, 2011). The study analyzed program curricula of three computing programs at a large research university to investigate the effects of a traditional curriculum on students' graduation and time to degree.

The study determined the effects of having a program-specific factor in the curriculum on graduation rates and student success. Among the three programs studied, the CS program has a program-specific factor "qualifying exam," which is a prerequisite for four or more advanced-level courses. The researcher studied whether having a program-specific factor affects students' mobility towards graduation or not. Institutional data, student flow visualizations and curricular analytic metrics were used to study the impact of program-specific factors in the program on the graduation rates and time to degree.

The researcher compared the curricular analytic metric values of three computing programs and investigated the effects of having a more stringent program curriculum on the graduation rates. Chi-square tests were conducted to determine statistical differences and significances between academic programs concerning metrics related to student success.

Research Question Three

The study developed an Adaptive Curriculum Refinement (ACR) approach for curricular improvement. The ACR design and development follows the curricular analytic design process, as described in Chapter Two. The complete methodology to develop ACR consisted of (a) intuitive data visualization to understand student degree mobility in the program and (b) network analysis of courses to study program curriculum.

Historical Data Mining to Understand Students' Degree Mobility Patterns

Universities have been using student cohorts to understand the factors affecting student success. Specifically, universities propose measures to improve student success measures based on student transitions between programs and colleges within the university. A visual representation of student transitions can help understand this concept better. Student flow visualizations are one way of visualizing student cohorts to better understand student transitions and propose measures to improve success metrics. Many recent studies in higher education have used these visualizations to make institutional related decisions to improve student and learning outcomes. In a study to evaluate student success metrics of CS and IT programs, the student flow visualizations were created to study student cohorts (Basavaraj, Badillo-Urquiola, Garibay, & Wisniewski, 2018). Based on these visualizations, recommendations were provided to the department to improve the program quality and college-level success metrics. These visualizations were used by Budapest University of Technology and Economics (Horvth, Molontay, & Szab, 2018), University of New Mexico (Heileman, Babbitt, & Abdallah, 2015), and the University of Central Florida (Basavaraj, Badillo-Urquiola et al., 2018; Basavaraj & Garibay, 2019) to understand various aspects of institutional effectiveness and quality improvement. Thus, student flow visualizations serve the purpose of providing easy understandability of institutional data to make program and institution-related decisions.

Network Analysis of Courses to Study Program Curriculum

The program curriculum is an institutional factor that has a potential impact on students' college completion (Akbaş et al., 2015). Studies have shown that universities have been using the curricular analytics framework to study the program curriculum (Akbaş et al.; Basavaraj & Garibay, 2018; Slim, Kozlick, Heileman, Wigdahl, & Abdallah, 2014). The curricular analytics framework makes use of complex network analysis and graph theory. The complex network analysis of courses is used to understand course relationships and prerequisite requirements of each course in the program curriculum.

The program curriculum is depicted in the form of a network with courses treated as nodes and connections (prerequisites and post-requisites) between courses as edges of a network. The blocking factor of a course is one of the well-defined curricular analytical metrics (Slim et al., 2014). The blocking factor of a course c_i in the program curriculum C_{prog} = (V, E) is defined by (Slim et al., 2014):

$$bl(c_i) = \sum_{c_i, c_j \in V} I\,(c_i, c_j) \tag{3.4}$$

$$where\ I = \begin{cases} 1 & if\ there\ exists\ edge\ from\ c_i\ to\ c_j \\ 0 & if\ there\ is\ no\ edge\ from\ c_i\ to\ c_j \end{cases} \tag{3.5}$$

The study introduced the new structural factor "Risk factor" to measure risk levels of each course in the program curriculum. The risk factor R_f of a course c_i in the program curriculum C_{prog} = (V, E) is defined as:

$$R_f\,(c_i) = Avg_{taken}(c_i) * bl(c_i) \tag{3.6}$$

Where $Avg_{taken}(c_i)$ is the average number of times a course taken by a distinct student and $bl(c_i)$ is the blocking factor. The significance of the risk factor is to measure the risk levels of each course in the program curriculum, and this factor can be used to compare two courses in the same curriculum. For example, if the risk-level of course-A is greater than course-B, then course-A is highly risky for students in regard to course completion and degree progression compared to course-B.

Decision-Making Process of Adaptive Curriculum Refinement

The Adaptive Curriculum Refinement system makes use of curricular analysis design process (Chang et al., 2016). The system makes decisions based on student degree mobility patterns and the network analysis of courses. First, the system analyzes the course performance data of students using student degree mobility patterns to understand the course performances of students who graduated and those who did not as shown below.

Algorithm Part 1 of Adaptive Curriculum Refinement Decision Process

---

procedure DEG-MOB (T, C_F, R_f)

T = {t1, t2, t3, t4, …. tn}

C_F = { c1, c2, c3, c4, c5……cn}

for each term

Calculate the number of students who dropped out of program.

for each student **do**

Create a set C_F

C_F : List all failed courses.

Calculate the risk factor R_f of all courses.

end for

end for

end procedure

Second, the system uses network analysis of courses as the second part in the decision-making process. The two important steps in the second part were (a) the system selects a set of courses that have high risk factors and (b) prerequisite, corequisite, and post-requisite analyses of courses with high risk factors. The overall working of the second part of the decision-making process is discussed below.

Algorithm Part 2 of Adaptive Curriculum Refinement Decision Process

Define C_n to be the list of courses within a curriculum.

Define M to be the adjacency matrix representation of the curriculum

Let Nc be the number of courses in a curriculum.

Initialize $t = N$

while C_n not empty and $t < N_c$ do

Calculate risk factor R_f for all courses in C_n

for all courses

Create two sets A and B

A: List all the courses that has risk factor greater than or equal to average risk factor of all courses [$R_f(c_i) > Average\ (R_f)$].

B: List all the courses that has risk factor less than the average.

for all courses in set A

Choose all courses that has connection from each course in set A to other courses in $C_{n.}$

Create set C.

C: List all courses that has connection between each course in set A and courses in $C_{n..}$

(A_{c1}: $c_1, c_2, c_3 \dots c_i$, A_{c1}: $c_1, c_2, c_3 \dots c_{i}, \dots A_{cn}$: $c_1, c_2, c_3 \dots c_i$)

for each course A_{cn} in C

for each course c_i in A_{cn}

Calculate $deg_{ci} = deg_i + deg_o$

(Add prerequisites and post requisites of c_i).

if $deg_{ci} = 1$ then

Create set D.

else

stop

if num (set D) is even (i.e., 2,4,6…) then

Assign co-requisite requirement for any two courses in set D.

else

stop (break)

end for

end for

end for

end for

$t = t+N$

end while

CHAPTER FOUR: IMPACT OF TRADITIONAL PROGRAM CURRICULUM ON STUDENT SUCCESS

The 'program curriculum' is one of the institutional factors that affect student success (Kuh et al., 2011). The analysis in this chapter helps to understand the effects of traditional program curriculum on student success by analyzing the program curriculum and institutional data of a large public university. The analysis focuses on understanding the relationship between metrics deduced based on network analysis of program curriculum and student success metrics such as graduation, and time to degree. Ultimately, the analysis and results would help the administrative staff, faculty and curriculum designers of higher education institutions in curriculum assessment and reform processes.

The current curriculum assessment for reform purposes involve focus groups, surveys, and interviews (Carpenter, Dopson, Kim, & Kniatt, 2016). Some academic programs evaluate based on students' mastery of content. The most commonly used modes to test students' mastery are pre-tests and post-tests. Historically, the curriculum evaluation for reform purposes is conducted using stakeholders (students, faculty), course profiles (Saunders, 2011). The current status of understanding the program curriculum based on analytics is limited (Komenda, et al., 2015; Toetenel & Rienties, 2016). Most higher education institutions review their curriculum at program level using student and faculty surveys, programs and teaching practices, surveys of the first-year experience and student perceptions of their program after graduation, program-level pass rates, and program completion data.

The analysis in this chapter considers institutional data to understand the degree progression of students in CS, IT, and CE programs and determines its relationship with the program curriculum metrics.

Assumptions

This chapter analyzes institutional data of CS, IT, and CE academic programs at a large public research university to understand the effects of traditional program curriculum on student degree progression and time to graduation. This study utilizes the following assumptions:

- Students were intrinsically motivated to complete their undergraduate degree.
  As discussed in Chapter Two, student motivation plays a vital role in completing a degree. A certain amount of motivation is required to retain and complete college. This chapter assumed that students had a certain amount of motivation intrinsically to complete their degree.
- Students were financially responsible for completing their degrees on time.
  Attending college is expensive. Most of the times students leave college due to financial hardships or unable to get financial support (Olbrecht, Romano, & Teigen, 2016). This chapter assumed that all students were either getting federal tuition support or using personal funds to attend college.
- Academic programs have a well-defined prerequisite and post-requisite curriculum flowcharts. Most academic programs especially computing programs have well-defined curriculum at a program level. This chapter utilized such curriculum to determine its effects on student graduation.

Analysis and Results

This chapter made use of network analysis of program curriculum and institutional data to study the effects of program curriculum on student success. This chapter used variables stated in Table 1 to create student flow visualizations in order to understand degree mobility patterns and to calculate student degree mobility turbulence values of such visualizations. In addition, the program curriculum was visualized in the form of a network to calculate the curriculum stringency values. The equations to calculate the curriculum stringency and student degree mobility turbulence values are explained in Chapter Three.

The study first examined the relationship between curriculum stringency and student degree mobility patterns of transfer and FTIC students enrolled in CS, IT, and CE academic programs. The curriculum stringency values were calculated for CS, IT, and CE program curricula. Table 4 provides curriculum stringency values of three academic programs. The curriculum stringency value of CS program curriculum is greater than IT and CE programs. CS program requires students to pass a program-specific factor 'qualifying exam' in addition to courses in the curriculum to graduate, whereas IT and CE programs requires students to pass only courses in the curriculum and do not have any program-specific requirement.

Table 4: Curriculum Stringency Values of Three Computing Programs

Academic Program	Program-specific factors?	Curriculum Stringency Value
Computer Science	Yes	2.36
Information Technology	No	1.04
Computer Engineering	No	1.39

Student flow visualizations were used to understand student degree mobility patterns within the institution. Figures 3, 5, and 7 represent the student flow visualizations of CS-transfer, IT-transfer, and CE-transfer students, respectively. Student flow visualizations of CS-FTIC, IT-FTIC, and CE-FTIC students are shown in Figures 4, 6, and 8, respectively.

The student mobility turbulence metric was calculated for CS-transfer, CS-FTIC, IT-transfer, IT-FTIC, CE-transfer, and CE- FTIC student groups. Table 5 summarizes normalized student mobility turbulence metric values of CS-transfer, CS-FTIC, IT-transfer, IT-FTIC, CE-transfer, and CE- FTIC student groups.

Table 5: Student Mobility Turbulence Metric Values of Six Student Groups (*c1*=1, *c2* = 0.5)

Academic Program	Student Status (FTIC or Transfer)	Student Mobility Turbulence Metric Value
Computer Science	FTIC	0.62
	Transfer	0.72
Information Technology	FTIC	0.59
	Transfer	0.89
Computer Engineering	FTIC	0
	Transfer	0.42

Understanding Student Flow Visualizations

Institutional data was visualized in the form of student flow visualizations (Morse, 2014) to understand student degree mobility patterns. The columns in student flow visualizations represent semesters (or terms) starting from fall 2013 to fall 2018. The columns were ordered by term starting from fall, spring and summer semesters (e.g., fall 2013, spring 2014, summer 2014). The rows in the visualizations represent academic programs. For example, concerning

Figure 3, the first column has only one row, which indicates CS program and in the second column there are six rows including dropped out, which indicates five different academic programs and a dropped out row. The links (or edges) between columns denote student transitions such as (a) student changed a major, (b) dropped out of target university, or (c) still in the current program.

The width of the rows represents the number of students and the width of each link between two rows represents the number of students who made transition. If there is a link passing from one row in a column to a different row in a different column then it means that those students either changed their major, dropped out of target university or graduated. For example, in Figure 3, there is a link from fall 2013 (Column-1) to IT (Column-2), which means some students changed their major from CS to IT program. If there is a link from any node to a dropout node that means a student dropped out of the target university. For example, in Figure 3, the link from Fa'2013 column to the dropout row in Sp'2014 column means a percentage of CS students dropped out of target university. Similarly, if there is a link from any node to a graduation node that means a student graduated from that respective academic program.

This study focused on understanding the degree mobility patterns of students in CS, IT and CE programs. Some students in these programs change majors to other non-computing areas like Accounting, Business etc. (Figure 3).

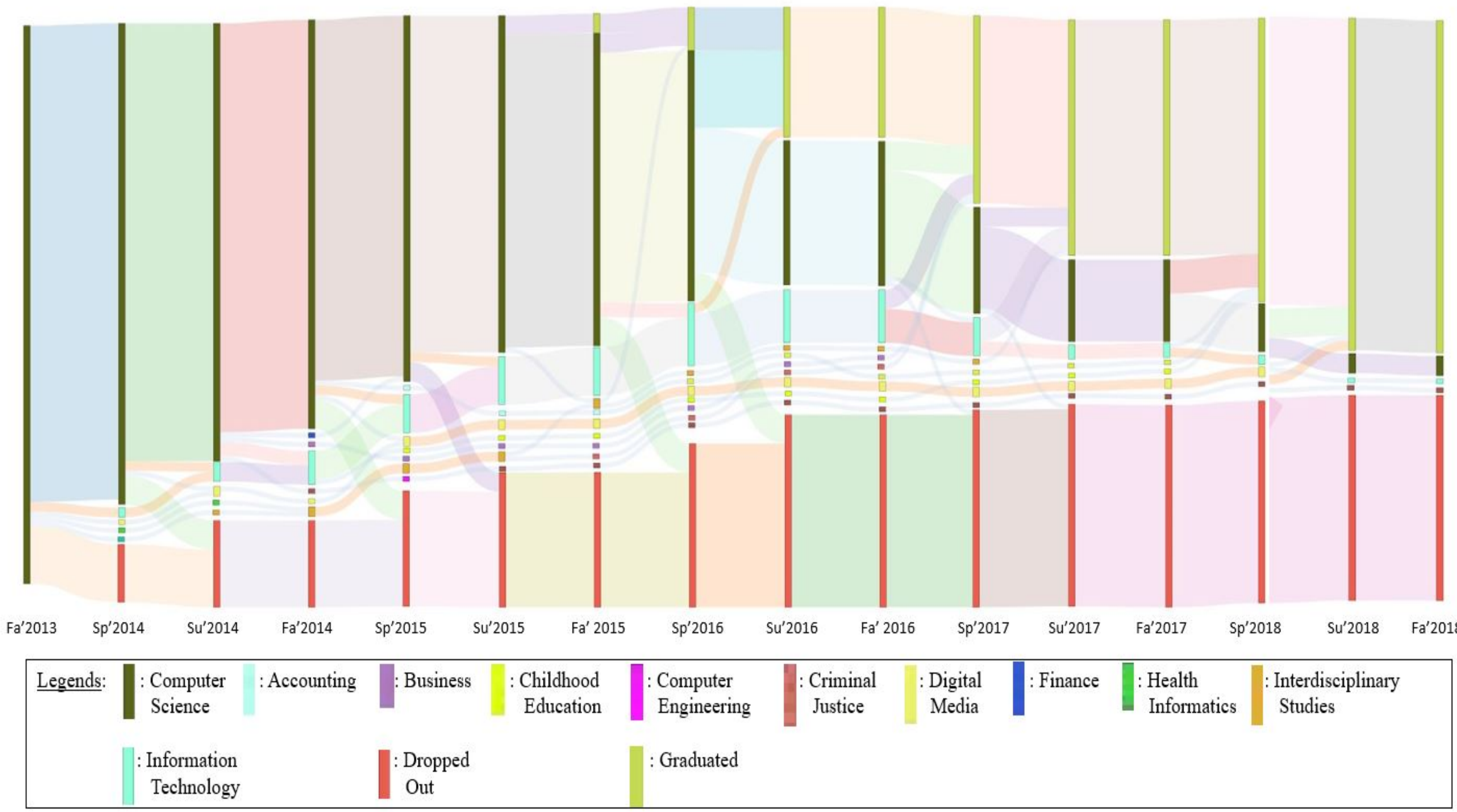


Figure 3: Student flow visualization of CS - transfer students.

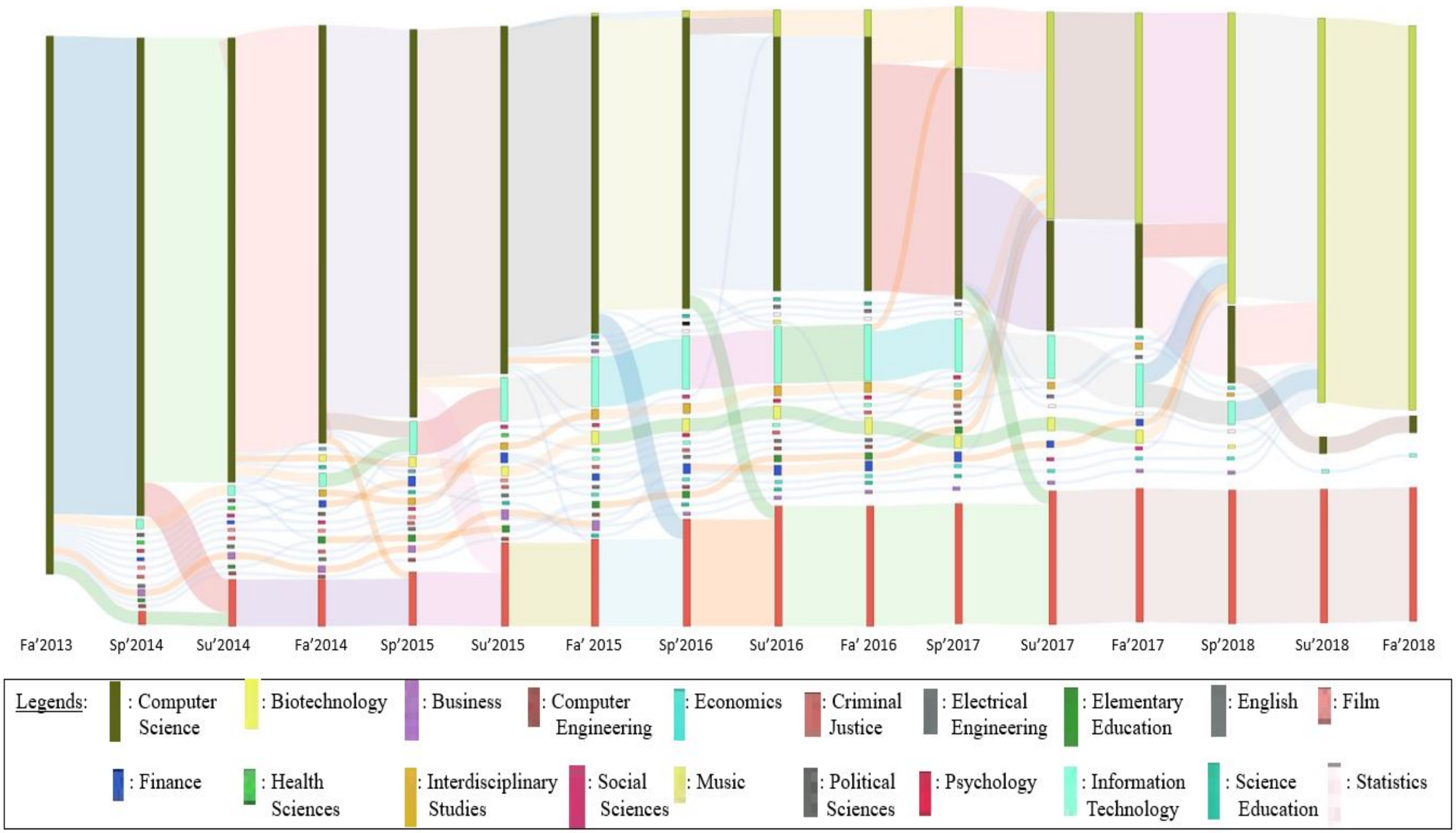


Figure 4: Student flow visualization of CS - FTIC students.

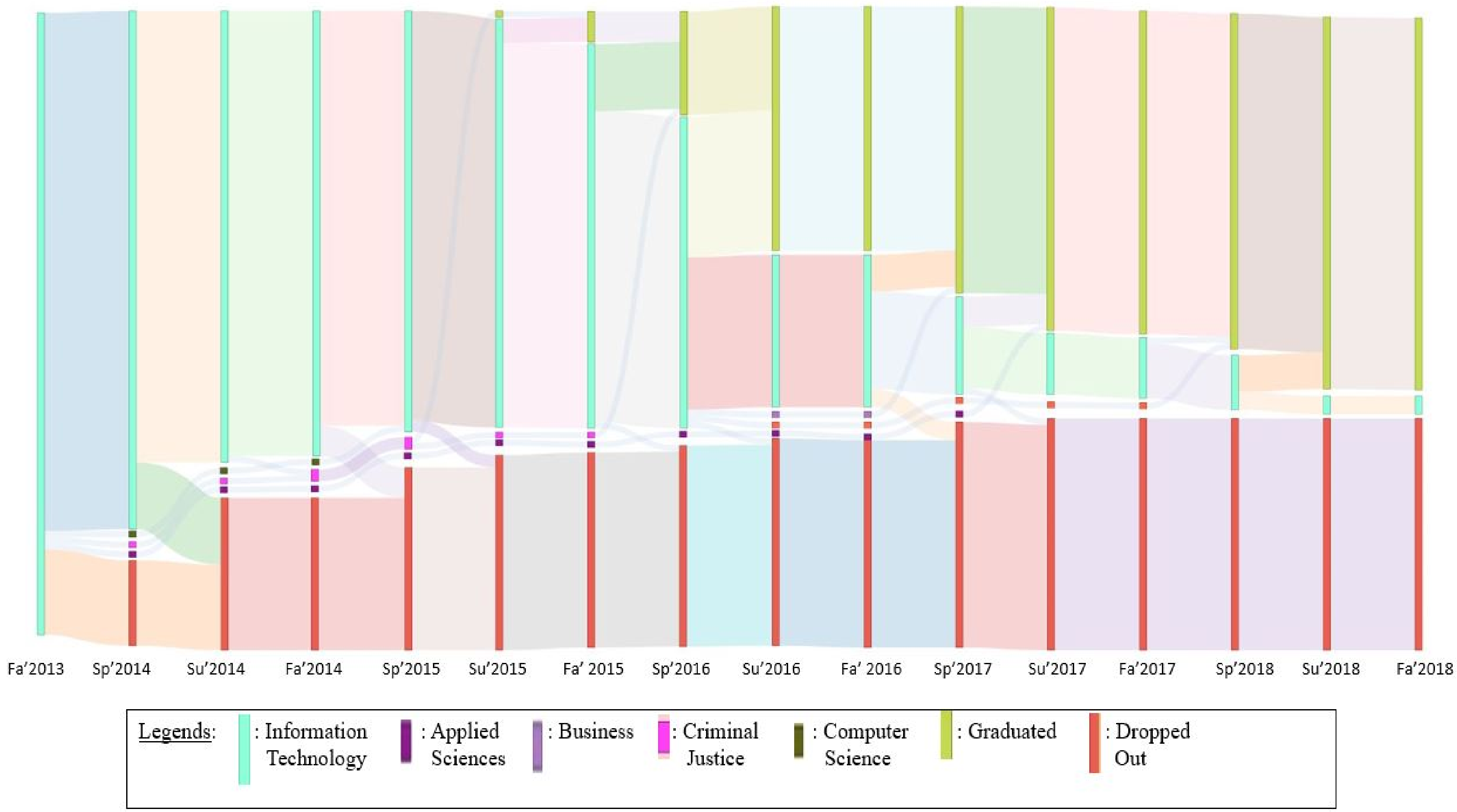


Figure 5: Student flow visualization of IT - transfer students.

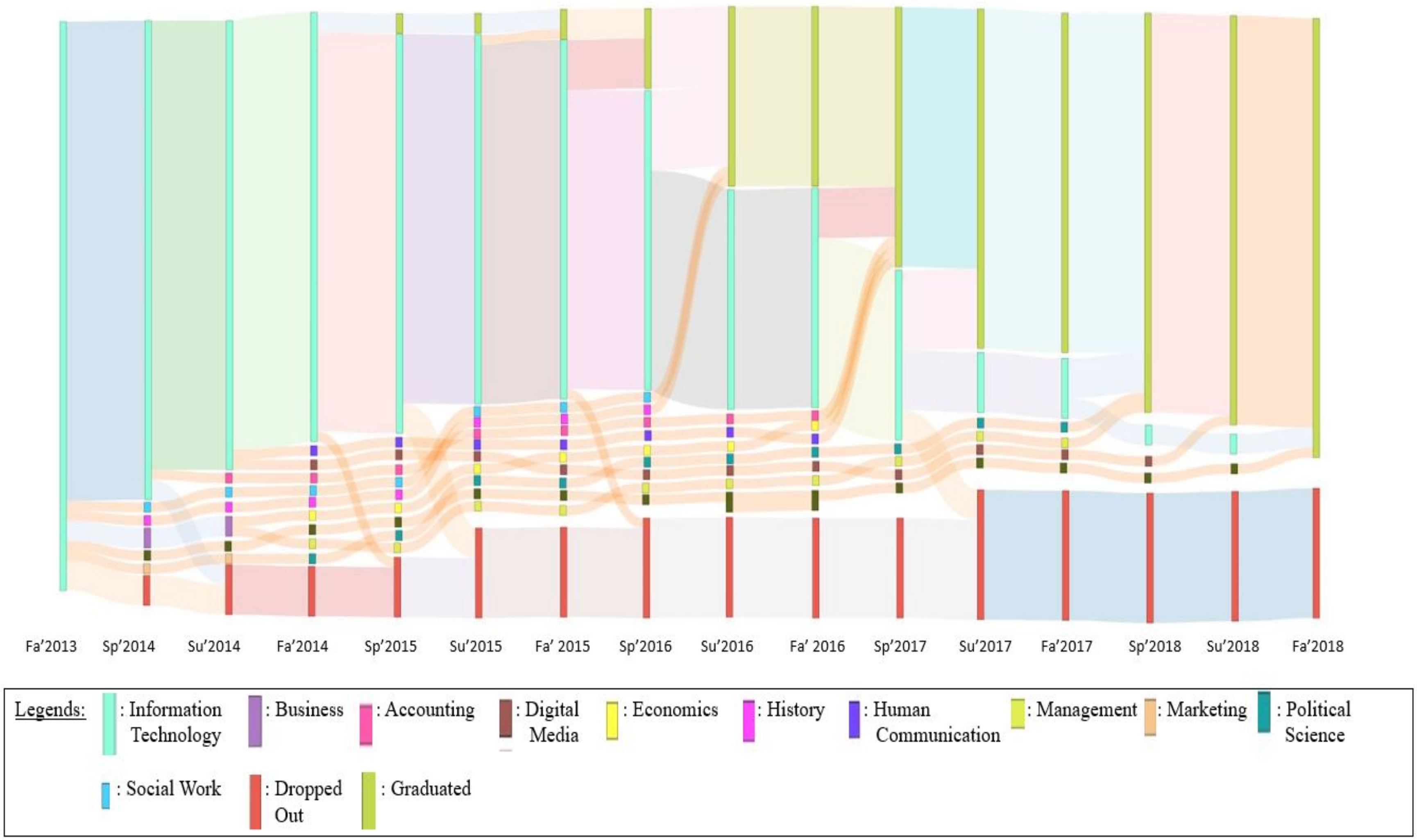


Figure 6: Student flow visualization of IT - FTIC students.

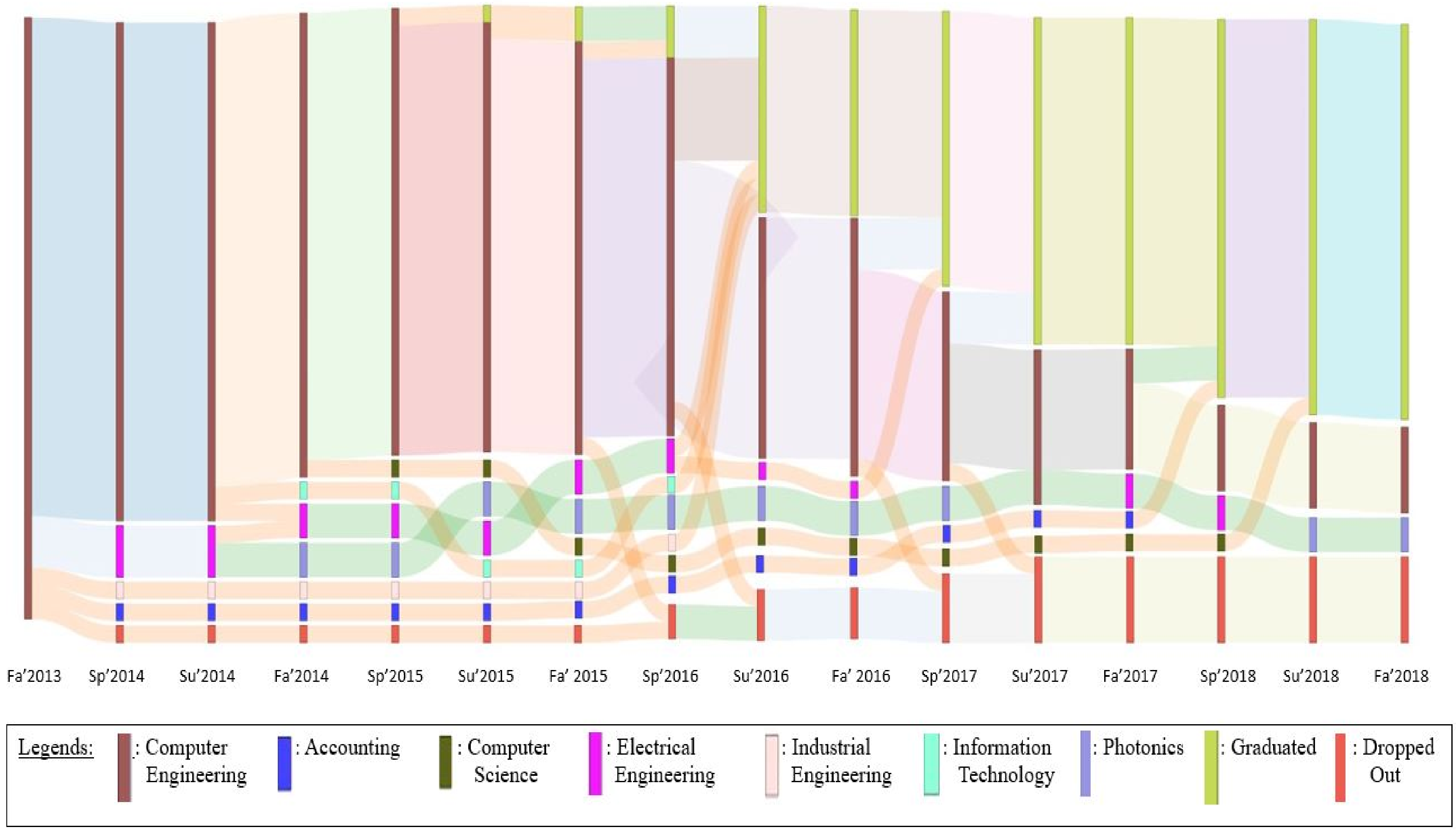


Figure 7: Student flow visualization of CE - transfer students.

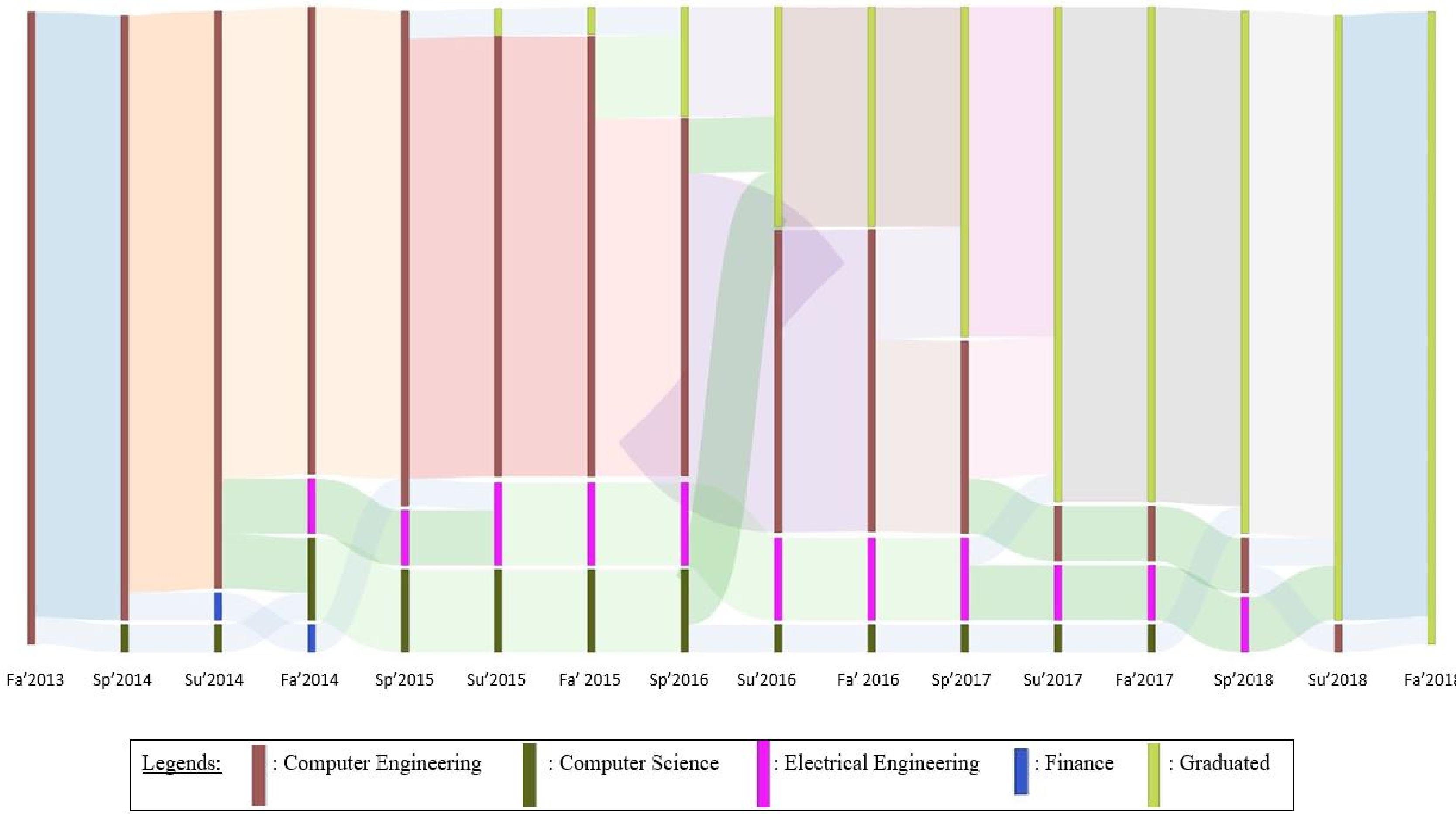


Figure 8: Student flow visualization of CE - FTIC students.

Computer Science Student Degree Mobility Patterns

CS Transfer Student Degree Mobility Patterns

CS transfer students began to drop out at the end of their first term (Fa'2013). In terms of dropout rates, 36% of transfer students dropped out. The number of students who dropped out was relatively high at the end of the first semester, and the dropout rate was ascending until the fall 2018 semester. Additionally, only 18% of students changed their major to other academic programs. Around 10% of students changed their major to the IT program, which is a sister program at the target university. Overall, 59% of transfer students graduated at the end of the fall 2018 term, and only 41% of them graduated in the CS program. The number of transfer students started graduating at a higher rate in their eighth term after starting their major. Figure 3 shows the student degree mobility patterns of CS transfer students.

CS FTIC Student Degree Mobility Patterns

In contrast, CS FTIC students began graduating at the end of the summer 2015 term. Nearly 23% of students changed their major to other programs, out of which 46% of them changed to IT. In terms of dropout rates, 25% of students dropped out by the end of the fall 2018 term. The number of students who dropped out was relatively high at the end of spring 2014 (10 students) and spring 2015 (nine students) terms. Additionally, 71% of students graduated at the end of the fall 2018 term, and 65% of them graduated with CS degrees. CS FTIC students changed their major from CS to 19 other academic programs, including IT and CE. FTIC students started graduating at a higher rate at the end of their 11th term after starting their major. Figure 4 shows the student flow visualization of CS FTIC students.

Information Technology Student Degree Mobility Patterns

IT Transfer Student Degree Mobility Patterns

Figure 5 shows the student degree mobility patterns of IT transfer students. IT transfer students began to drop out at the end of their first term (Fa'13). More than a quarter, 37%, of IT transfer students dropped out at the end of the fall 2018 term. At the end of first and second terms, 37% and 27% of students, respectively, started dropping out of the IT program. Only six out of 102 (6%) students changed their major from IT to other programs. In terms of graduation, 60% of students graduated at the end of the fall 2018 term, out of which 92% of them graduated with IT degrees. Students started graduating at a higher rate in the eighth term (Sp'16) after starting their major.

IT FTIC Student Degree Mobility Patterns

IT FTIC students began graduating at a higher rate at the end of eighth (Sp'16) and 11th (Sp'17) terms after starting their major. Out of the total students who started their major in the IT program, 77% of students graduated at the end of the fall 2018 term. The majority (77%) of those students graduated with IT degrees. In terms of dropout rates, 23% of students dropped out of college at the end of the fall 2018 term. Only 16% of students changed their major from IT to other programs, and the majority (77%) were successful in getting their degree in those programs. IT FTIC students changed their major from IT to 10 other academic programs. Figure 6 shows the student degree mobility patterns of IT FTIC students.

Computer Engineering Student Degree Mobility Patterns

CE Transfer Student Degree Mobility Patterns

CE transfer students began to graduate at the end of the fifth term (Sp'15). Nearly 26% (six students) of students graduated at the end of the eighth term (Sp'16). Overall, 66% of students graduated, out of which 74% of students graduated with CE degrees. In terms of dropout rates, only 14% (five students) dropped out of college. Students start to drop out of college at the end of their first term (Fa'13). Only 23% of students changed their major from CE to other programs. CE transfer students changed their major from CE to the other six programs, including CS and IT programs. Figure 7 shows student degree mobility patterns of CE transfer students.

CE FTIC Student Degree Mobility Patterns

Figure 8 illustrates the student degree mobility patterns of CE FTIC students who started their major in the fall 2013 term. All CE FTIC students of the fall 2013 cohort graduated at the end of the fall 2018 term. Only 26% (six students) changed their major from CE to other programs, and these students were successful in getting degrees in those programs. Out of the total students who started in the CE program, 74% of them were successful in getting a degree in CE. CE FTIC students changed their major from CE to only three other academic programs, including CS.

Comparison of CS, IT and CE Student Degree Mobility Patterns

Comparison of CS, IT, and CE Transfer Student Degree Mobility Patterns

Overall, CS transfer students tended to have a longer path to graduation than IT and CE transfer students. The percentage of students who graduated after starting their majors in one of three academic programs was more significant for the CE program (66%) than the CS (59%) and IT (60%). However, the percentage of students who started their major in IT tended to graduate in IT (55%) at a higher rate compared to CS (41%) and CE (49%) students who started in CS and CE, respectively.

In terms of students switching majors, 22% of CE transfer students changed their majors from CE to others, whereas only 18% and 5% of CS and IT students changed their majors. CS and IT students changed their majors to a wide variety of computing and non-computing programs, whereas CE students stayed in computing programs.

The dropout rates of CE transfer students (14%) were lower than IT (37%) and CS (36%) students. Both CS and IT transfer students stayed longer in their programs before dropping out. However, this behavior was significant for CS students.

Comparison of CS, IT, and CE FTIC Student Degree Mobility Patterns

CS FTIC students tended to change their majors to a wide variety of programs compared to CE and IT programs. The major-changing behavior of FTIC students was significant in all three programs. CS and IT students seemed to prefer non-computing academic programs after they decided to leave the current major, whereas CE students preferred to stay in computing programs.

In terms of graduation, CE FTIC students (100%) tended to graduate at a higher rate compared to students in CS (71%) and IT (77%) programs. Even when students change their major to other programs, CE FTIC students seemed to graduate in less time (number of terms) compared to the other two programs. The percentage of students who started their major in CS and graduated in CS (47%) was lower compared to students who started and graduated in the CE (74%) and IT (60%) programs. The dropout rate of CE FTIC students was zero, whereas the dropout rates of CS and IT students were 25% and 23%, respectively.

Comparison of Transfer and FTIC Student Degree Mobility Patterns

Student mobility turbulence metric values of transfer students in CS, IT, and CE programs was greater than FTIC students in their respective programs, which means transfer students drop out in large number compared to FTIC students. The majority of FTIC students tend to change their majors whereas transfer students tend to drop out in large numbers instead of changing majors. There exists a statistical difference between FTIC and transfer students of CS, IT, and CE programs in terms of graduation rates.

Student Success Metrics

Table 6 summarizes the percentage of graduated and not graduated students who started in CS, IT, and CE programs during the fall 2013 term. All CE-FTIC students who started as CE majors graduated, whereas 59% of CS-transfer students graduated.

Table 6: Percentage of Students Graduated and Not Graduated Who Started in CS, IT, and CE Programs During Fall 2013 Term

Program	Transfer/FTIC	Graduated	Not Graduated
CS	Transfer	59% (CS: 41%)	41%
CS	FTIC	71% (CS: 47%)	29%
IT	Transfer	60% (IT: 55%)	40%
IT	FTIC	77% (IT: 60%)	23%
CE	Transfer	66% (CE: 49%)	34%
CE	FTIC	100% (CE: 74%)	0%

Chi-square tests were conducted to determine statistical difference. The p-values of the chi square tests between two programs are shown in Table 7 for the alternate hypothesis that (academic program- student type)$_1$ is different from (academic program- student type)$_2$ in terms of graduation [null hypothesis: (academic program- student type)$_1$ is same as (academic program- student type)$_2$, , $\alpha = 0.05$]. Gray cells indicated where there was no evidence for supporting the null hypothesis at a significance level at $\alpha = 0.05$. Based on the results of chi-square tests, there exists statistical differences between FTIC and transfer students within each program in terms of graduation. But there is no statistical difference observed among transfer students in the three programs. For FTIC students, there exists a statistical difference between CS and CE, and IT and CE in terms of students' graduation. Based on these, one can conclude that the transfer and FTIC students in the same cohort experienced different levels of student success. Also, the degree mobility patterns of transfer and FTIC students were different, which means the degree progression characteristics of transfer students were different from FTIC students.

Table 7: P-Values of Chi-square tests to determine significance of difference between transfer and FTIC students in CS, IT, and CE programs in terms of graduation (alternate hypothesis that two programs are different in terms of students graduation; null hypothesis that two programs are same in terms of graduation, α = 0.05). Grey cells indicate agreement of the alternate hypothesis.

Programs	CS-T	CS-FTIC	IT-T	IT-FTIC	CE-T	CE-FTIC
CS-T		0.026344	0.859232	0.016254	0.452255	0.000137
CS-FTIC			0.050898	0.3999	0.502062	0.003076
IT-T				0.026395	0.535577	0.000208
IT-FTIC					0.229529	0.012326
CE-T						0.001615
CE-FTIC						

Summary

The first research question set out to determine how the traditional program curriculum impacts students' degree mobility in undergraduate computing programs at a large public university. Traditional curricula were likely to affect the degree mobility of both transfer and FTIC students. In other words, the traditional program curricula were likely to affect students' change of major and dropout behaviors. The scale of effect was significantly larger for transfer students compared to FTIC students.

There exist both statistical and structural (or visual) differences between transfer and FTIC students of all three programs in regard to student mobility through the programs. Also, all three program curricula studied have high stringency values, which means there is a high tendency for students in these programs to either drop out or change majors. The CS program was more stringent than the CE and IT programs, which means there is less chance that students who started as CS majors graduate with a CS degree, whereas the chances to graduate in the same major are better for CE and IT majors.

CHAPTER FIVE: IDENTIFYING DRAWBACKS OF TRADITIONAL PROGRAM CURRICULUM

Multiple factors affect student success including the program curriculum (Wigdahl, Heileman, Slim, & Abdallah, 2014; Akbaş et al., 2015). This chapter helps to understand some of the drawbacks of traditional program curriculum in achieving maximum student success by analyzing the program curriculum and institutional data of a large public university. This chapter focuses on understanding the effects of traditional program curriculum of CS, IT, and CE undergraduate programs on students' time to graduation and credit accumulation. In this chapter, student success is measured in terms of time to graduation and credit accumulation behavior of students. Ultimately, the analysis and results would help the administrative staff, faculty and curriculum designers of higher education institutions to understand how the traditional program curriculum could affect students' time to graduation and credit accumulation and take necessary measures to improve the curriculum at a program level.

Some undergraduate academic programs have a program-specific requirement (e.g., qualifying exams, assessment exams, etc.) in their curriculum in addition to courses whereas other programs do not have any such additional requirement. This chapter studied the effects of (a) a program curriculum with an additional requirement 'program-specific factor' on students' time to graduation and credit accumulation; (b) a curriculum without any additional requirement on students' time to graduation and credit accumulation.

Assumptions

This study utilizes the following assumptions:

- Students were intrinsically motivated to complete their undergraduate degrees.
  As discussed in Chapter Two, student motivation plays a vital role in completing a degree. A certain amount of motivation is required to retain and complete college. This chapter assumed that students had a certain amount of motivation intrinsically to complete their degrees.
- Students were financially responsible for completing their degrees on time.
  Attending college is expensive. Most of the time, students leave college due to financial hardships or unable to get financial support (Olbrecht et al., 2016). This chapter assumed that all students were either getting federal tuition support or using personal funds to attend college.
- Academic programs have a well-defined prerequisite and post-requisite curriculum flowcharts. Most academic programs especially computing programs have a well-defined curriculum at a program level. This chapter utilized such a curriculum to determine its effects on student graduation.
- All three computing programs considered in this study are similar in terms of academic quality and treated equally by the institutional administration. Some departments treat programs unequally in terms of resource allocation etc., due to which sometimes negative social comparisons start to spread within the department (Basavaraj et al., 2018). This

assumption was made to convince the reader that all three programs were considered equally in terms of quality and value.

Analysis and Results

This chapter made use of (a) network analysis of courses to study the program curriculum; and (b) institutional data to calculate students' time to graduation and credits accumulated by students of CS, IT, and CE undergraduate programs. This chapter used variables stated in Table 1 to calculate students' time to graduation and credit accumulation. In addition to fall 2013 cohort data, institutional data of academic years 2004–2012 of the Computer Science program were used to study the effects of a program-specific factor in the program curriculum on the graduation rates (see Table 8). A total of 4,557 student records comprised a sample, which included both transfer and FTIC students.

Table 8: Program Variables used to study the effects of program-specific factor on students' time to graduation and time to graduation

Variable	Description
Academic program	Student's primary program.
Admit term	Term when students received admission offer for the term, they applied
Program enrollment semester-wise	Term-wise program enrollments
Program start term	Term when students first enrolled in the program
Qualifying exam attempt term	Term when students attempted the CS qualifying exam
Qualifying exam result	Qualifying exam result (pass(4.0)/fail (0))

This chapter first calculated the students' time to graduation of CS, IT, and CE programs. Then the effect of program-specific factor on students' time to graduation and credit accumulation were studied. In addition, the curriculum metrics deduced in Chapter Four were used to explain the drawbacks of traditional program curriculum in terms of students' time to degree and credit accumulation behavior.

Time to Graduation

The time to graduation was calculated for CS, IT, and CE students of the fall 2013 cohort (as shown in Table 9). Students in the CS program take longer to graduate than CE and IT majors. Also, CS students who changed their major to other academic programs take longer than students in other majors to complete the program. IT majors take relatively less time to complete their programs compared to CE and CS. Also, IT majors who changed their major to other programs take lesser time to graduate than CS and CE majors who changed to other programs.

Table 9: Average Time to Graduation (in terms of semesters) of CS, IT, and CE Programs

Start Program	Graduated Program	Average Time to Graduation (Semesters)
CS	CS	10.05
CS	other than CS	10.65
IT	IT	7.57
IT	other than IT	9.08
CE	CE	8.53
CE	other than CE	9.60

Network Analysis of Program Curriculum

The program curriculum structure (program flowchart) was visualized in the form of a network. Each course was treated as a node in the network and an edge between two nodes represents either prerequisite or post-requisite requirements. For example, in Figure 9, course-1 and course-2 are prerequisites for course-3 and course-4 is the post-requisite of course-3.

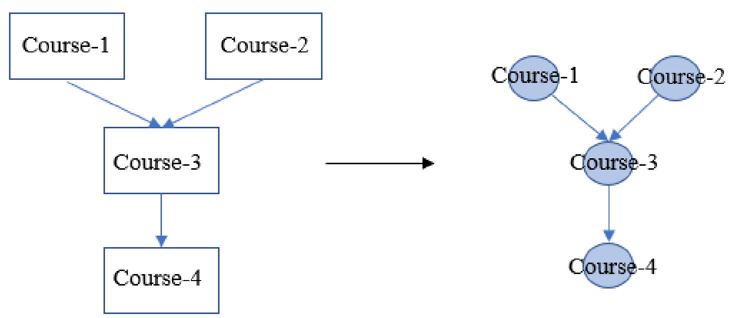


Figure 9: Network Analysis of Program Curriculum

The program curriculum of CS, IT and CE programs were visualized in the form of a network (see Figure 10). Courses in the program curriculum were represented as nodes in the network, and the prerequisite requirements between courses were represented by edges in the network. For example, in Figure 10, if course-28 is a prerequisite of course-29, then there exists a directed edge from course-28 to course-29 in the network.

CE Program Curriculum

The researcher visualized CE program curricula in the form of a network (as shown in Figure 10). Each node in the network represents a course in the curriculum. For example, course-17 in the network represents a course in the program curriculum. A directed edge connects two nodes. For example, in Figure 10, there exists an edge from course-11 to course-12, which means course-11 is a prerequisite for course-12.

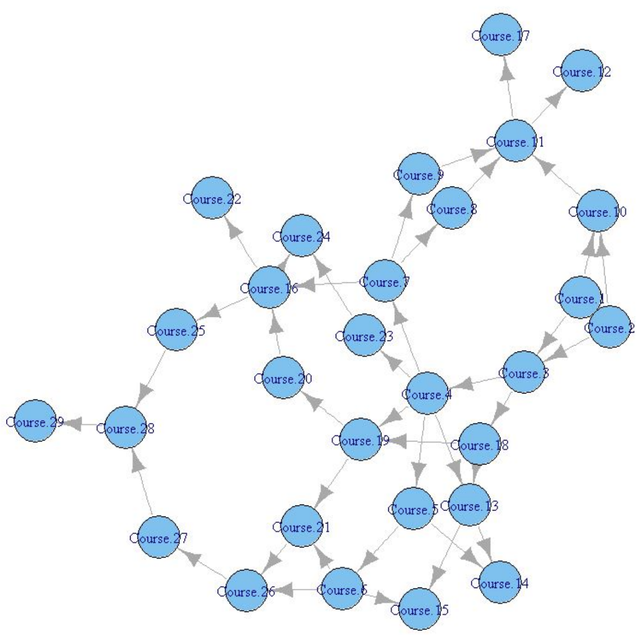


Figure 10: Network representation of CE program curriculum.

One of the curricular analytics metrics, "course-cruciality," (Wigdahl et al., 2014) was calculated for all the courses in the program curriculum (see Figure 11). These cruciality values were used to determine the effect of each course (node's impact) on all other courses in the curriculum, and to compare the course's impact on students' graduation.

CE course names are provided in Table 10.

Table 10: CE Course Names

Course	**Course Name**
Course-1	Math-1a
Course-2	Math-1b
Course-3	Calculus-1
Course-4	Calculus-2
Course-5	Calculus with Analytic Geometry
Course-6	Differential Equations-1
Course-7	Engineering Analysis and Computation
Course-8	Object Oriented Programming
Course-9	Computer Science-1
Course-10	Intro to Discrete Structures
Course-11	Computer Science-2
Course-12	Processes OO DW
Course-13	Engineering Analysis and Statistics
Course-14	Engineering Analysis and Dynamics
Course-15	Thermo Fluids
Course-16	Computer Organization
Course-17	Operating Systems
Course-18	Physics-1
Course-19	Physics-2
Course-20	Digital Systems
Course-21	Electrical Networks
Course-22	Computer Architecture
Course-23	Prob and Stats for Engineers
Course-24	Computer Communication Networks
Course-25	Embedded Systems
Course-26	Networks and Systems
Course-27	Electronics-1
Course-28	Senior Design-1
Course-29	Senior Design-2

The higher the cruciality value of a course, the higher its impact on other courses. For example, the cruciality value of course-4 is greater than that of course-18, which means the impact of course-4 is high on CS courses compared to the impact of course-18. More than 50% of courses (16 courses) in the CE curriculum have equal cruciality values (see Figure 11).

The practical significance of course cruciality factor is to help curricular designers and faculty to understand the importance of each course in the curriculum and its impact on students' graduation.

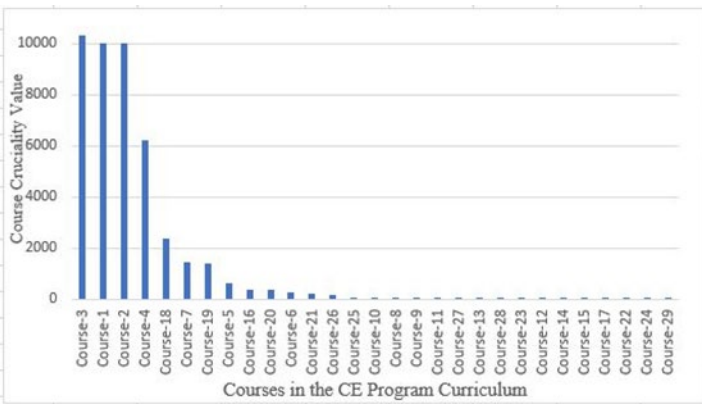


Figure 11: Course cruciality values of CE courses.

<u>CS Program Curriculum</u>

The researcher visualized CS program curriculum in the form of a network. CS program network consists of 26 courses (see Figure 12) and has a program-specific factor (course-15). Studies have shown that this program-specific factor is crucial in deciding students' time to graduation (Basavaraj, Ozmen, Garibay, & Georgiopoulos, 2018).

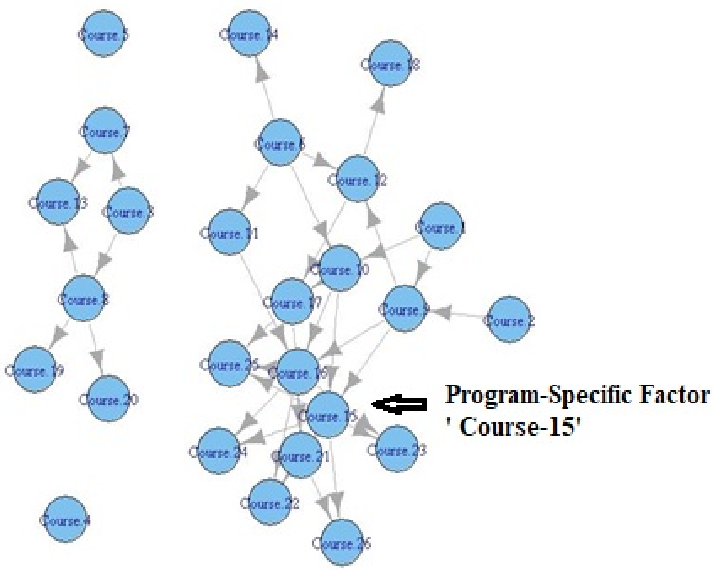


Figure 12: Network representation of CS Program curriculum.

The cruciality values of CS courses are shown in Figure 13. For example, course-6 has the highest cruciality value compared to other CS courses. Around 13 out of 26 courses have the same cruciality value. Even though the cruciality value of course-15 is lower than other courses, course-15 tends to affect students' graduation at a higher rate (Basavaraj, Ozmen et al., 2018). CS course names are provided in Table 11.

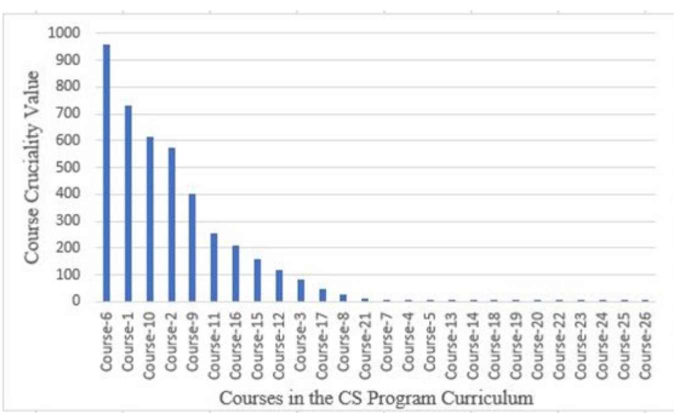


Figure 13: Course cruciality values of CS courses.

Table 11: CS Course Names

Course	Course-Name
Course-1	Math-1a
Course-2	Math-1b
Course-3	Calculus-1
Course-4	Tech Report Writing
Course-5	Statistical Methods-1
Course-6	Intro to C Programming
Course-7	Physics-1
Course-8	Calculus-2
Course-9	Intro to Discrete Structures
Course-10	Computer Science-1
Course-11	Object Oriented Programming
Course-12	Computer Organization
Course-13	Physics-2
Course-14	Security in Computing
Course-15	Foundation Exam
Course-16	Computer Science-2
Course-17	Systems Software
Course-18	Computer Architecture
Course-19	Calculus with Analytic Geometry
Course-20	Differential Equations-1
Course-21	Senior Design-1
Course-22	C++
Course-23	Discrete Computational Structures
Course-24	Programming Languages-1
Course-25	Operating Systems
Course-26	Senior Design-2

IT Program Curriculum

Figure 14 shows the network representation of the IT program curriculum. There are 25 courses in the curriculum. Each course is represented as a node, and a directed edge between two nodes represents a prerequisite requirement in the network. For example, course-16 is a prerequisite for course-25. Course-3, course-5, and course-6 are isolated nodes in the network, which means these nodes do not have any prerequisites. IT course names are provided in Table 12.

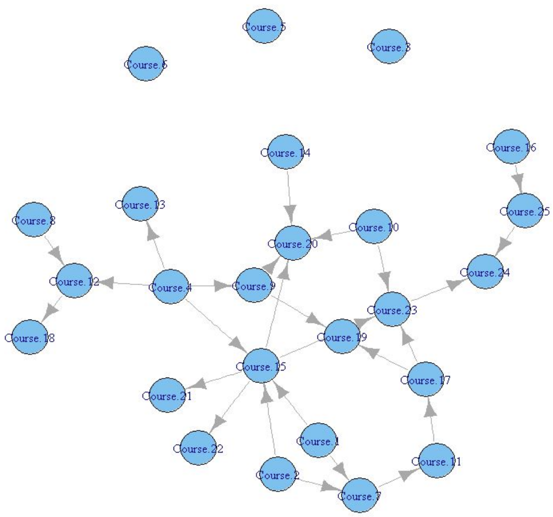


Figure 14: Network representation of IT program curriculum.

The course cruciality values of the IT course are shown in Figure 15. For example, course cruciality of course-4 is higher than course-1 and other courses. The isolated nodes such as course-3, course-5, and course-6 have equal cruciality values.

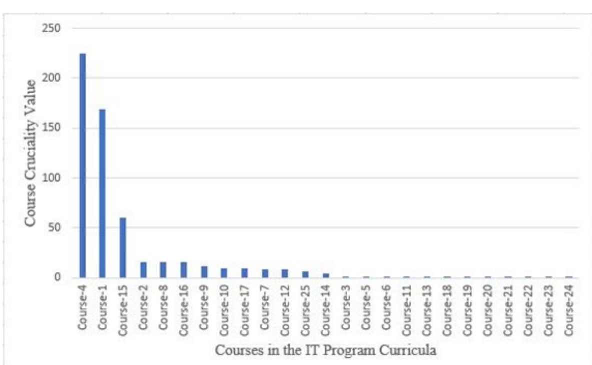


Figure 15: Course cruciality values of IT courses.

Table 12: IT Course Names

Course	Course Name
Course-1	Math-1a
Course-2	Math-1b
Course-3	Statistical Methods-1
Course-4	Intro to C Programming
Course-5	Macroeconomics
Course-6	General Psych
Course-7	Physics-1
Course-8	Databases
Course-9	Object Oriented Programming
Course-10	Discrete Mathematics
Course-11	Physics-2
Course-12	Foundations of IT
Course-13	Security in Computing
Course-14	Computer Architecture
Course-15	Computer Science-1
Course-16	Operating systems
Course-17	Computer Network Concepts
Course-18	Managing IT Integration
Course-19	Web-based IT
Course-20	Enterprise Computing
Course-21	Ethics in Science and Tech
Course-22	Foundations of HI
Course-23	Network-1
Course-24	Frontiers in IT
Course-25	System Administration

Comparison of Program Curricula: Effects of Program-Specific Factor on Graduation

CS program at the targeted university has a program-specific factor (i.e., CS qualifying exam) in the curriculum. This factor is similar to a course student had to pass in order to take advanced-level courses. The graduation rates of the CS program are dependent on this program-specific factor.

Around 31% of students attempted the exam and failed during the academic years 2004-2013. Out of the 31%, only 32% of students were still enrolled in CS, 13% of students were non-CS majors, and the remaining 55% of students either dropped out or graduated in other programs. Nearly half, 40%, of students were eligible to take the exam, but they delayed taking it, which may be due to the fear of failing.

Also, the researcher investigated the effects of (a) having a program-specific factor in the program curriculum and (b) computing curriculum on students' time to graduation. Institutional data were analyzed to determine whether program curriculum with high stringent values (> 1.0) impacts students' credit accumulation. Table 13, Table 14, and Table 15 show the credit accumulation of CS, CE, and IT students, respectively.

Chi-square tests were conducted to determine the statistical difference. Chi-square tests were conducted for students who changed their major from their primary programs to others and graduated to determine the statistical difference in terms of credit accumulation. The p-values of chi-square tests between two programs for students who changed their major and graduated and their credit accumulation are shown in Table 17 for the alternate hypothesis that two academic programs are different in terms of credit accumulation for students who changed their major and graduated (null hypothesis: two programs are similar in terms of credit accumulation for students who changed their major and graduated). Gray cells indicate that there was no evidence for supporting the null hypothesis at a significance level at $\alpha = 0.05$. Based on the results, there was no statistical difference for CS and IT, CE and IT students who changed their major and graduated in terms of credit accumulation. However, there exists a statistical difference between CS and CE students.

Chi-square tests were conducted between three programs for the number of students who graduated in their primary programs to determine the statistical difference in terms of credit accumulation. The p-values of chi-square tests between two programs for students who graduated in their primary programs and their credit accumulation are shown in Table 18 for the alternate hypothesis that two academic programs are different in terms of credit accumulation for students who graduated in their primary programs (null hypothesis: two programs are similar in terms of credit accumulation for students who graduated in their primary programs). Gray cells indicate that there was no evidence for supporting the null hypothesis at a significance level at $\alpha = 0.05$. Based on the results, there was no statistical difference for CS and CE, CE and IT students who graduated in their primary programs in terms of credit accumulation. However, there was a statistical difference between CS and IT students.

Table 13: Credit Accumulation of CS Students

CS Exam Attempted?	Passed?	Status After Attempting the Exam	Accumulated Credits
Yes	No	Still in CS	69% (Credits > 120)
			31% (Credits < 120)
Yes	No	Changed major	59% (Credits > 140)
			41% (Credits < 140)
Yes	Yes	Graduated	70% (Credits > 120)
			30% (Credits = 120)
Yes	Yes	Graduated	33% (Credits > 150)
			67% (Credits < 150)

Note. Required credits for graduation in the CS program (as of 2013) was 120 credits.

Table 14: Credit Accumulation of CE Students

Initial Student Status	Graduation Status (Yes/No)	Graduated Program	Accumulated Credits
CE major	Yes	CE	70% (Credits > 128)
			30% (Credits <= 128)
CE major	Yes	CE	44% (Credits > 140)
			54% (Credits <= 140)
CE major	Yes	Other than CE	39% (Credits > 140)
			61% (Credits <= 140)

Note. Required credits for graduation in the CE program (as of 2013) was 128 credits.

Table 15: Credit Accumulation of IT Students

Initial Student Status	Graduation Status (Yes/No)	Graduated Program	Accumulated Credits
IT major	Yes	IT	82% (Credits > 120)
			18% (Credits <= 120)
IT major	Yes	IT	51% (Credits > 140)
			49% (Credits <= 140)
IT major	Yes	Other than IT	45% (Credits > 120)
			55% (Credits <=120)
IT major	Yes	Other than IT	10% (Credits > 140)
			90% (Credits <= 140)

Note. Required credits for graduation in the CE program (as of 2013) was 120 credits.

Table 16: Curriculum Stringency Values of Six Computing Programs

Academic Computing Program	Curriculum Stringency Value
CS	2.36
IT	1.04
CE	1.39
Engg1-A	1.59
Engg1-B	1.50
Engg1-C	1.48

Table 17: P-Values of Chi-square tests to determine the significance of the difference between CS, IT, and CE programs in terms of credit accumulation of students who changed their major (the alternate hypothesis that two programs are different in terms of credit accumulation of students who changed their major; null hypothesis that two programs are same in terms of credit accumulation of students who changed their major, $\alpha = 0.05$). Grey cells indicate agreement of the alternate hypothesis.

Programs	CS	CE	IT
CS		0.022444	0.293226
CE			0.163752

Table 18: P-Values of Chi-square tests to determine the significance of the difference between CS, IT, and CE programs in terms of credit accumulation of students who graduated in their primary program. (the alternate hypothesis that two programs are different in terms of credit accumulation of students who graduated in their primary program; null hypothesis that two programs are same in terms of credit accumulation of students who graduated in their primary program, $\alpha = 0.05$). Grey cells indicate agreement of the alternate hypothesis.

Programs	CS	CE	IT
CS		0.348952	0.024119
CE			0.369783

Summary

Institutional data were used to understand the impact of traditional program curriculum on various student success metrics such as time to graduation and credit accumulation. Also, the effect of a program-specific factor in the program curriculum on graduation was studied. The study found that the higher the stringency, the longer the time to graduation. The study determined that the majority of computing programs have a highly stringent curriculum, which means students had to satisfy various program requirements (including a program-specific factor in some programs) in terms of courses to graduate. Thus, most computing curricula at the target university are stringent.

Traditional computing curricula of CS, CE, IT were likely to affect students' time to graduation. This is due to many prerequisites and post-requisite requirements of courses in computing programs. The CS program at the target university has a high curriculum stringency value compared to other programs because CS has a program-specific factor. The study determined that having a program-specific factor in the curriculum affects students' time to graduation and the graduation rates.

Another factor, "credit accumulation," was studied to determine the effect of the traditional curriculum on student graduation. The results show that the curriculum stringency does not affect students' credit accumulation towards graduation. Students tend to accumulate additional (more) credits than required for graduation irrespective of the curriculum stringency in the case of CS, IT, and CE programs. However, CS students who changed their majors tend to accumulate more credits than the other two programs, and there exists a statistical difference between CS and IT programs in terms of credit accumulation for graduated students. This could be due to the presence of a program-specific factor in the program curriculum. Future research may want to examine the effects of a program-specific factor on course enrollment in courses other than prescribed courses in the curriculum.

CHAPTER SIX: DEVELOPMENT OF ADAPTIVE CURRICULUM REFINEMENT SYSTEM

The 'curriculum reform' process at a program level is one of the most expensive and complicated processes in higher education institutions (Logue, 2018). This chapter focuses on the development of a system for CS, IT, and CE programs to assist curriculum designers, administrative staff, etc. in the curriculum reform at a program level. The adaptive curriculum refinement development process made use of network analysis of courses, and institutional data to come up with a solution to lower time to graduation for students who wish to graduate in their primarily enrolled academic program. Ultimately, the analysis and results would help the administrative staff, faculty and curriculum designers of higher education institutions in curriculum assessment and reform processes.

This chapter provides a review of the curriculum design analysis process (explained in detail in Chapter Two). The curriculum design analysis process consists of total of five stages: (a) data extraction and preparation; (b) data analysis; (c) data visualization; (d) interventions and; (e) expansion and refine. The data extraction stage consists of extracting data from data storage centers and then transforming to have consistent data reference types. Then data was prepared to answer strategic questions. In the data analysis stage, data were analyzed using inferential statistics, descriptive statistics, or data mining techniques. In the next step, data visualization helps to integrate human experience and knowledge with machine intelligence. The data analyses and visualizations are used by domain experts and researchers to implement actions for improvements in the interventions stage. Finally, all stages from (a) to (d) are revisited to evaluate the results. The development of an adaptive curriculum refinement follows the curriculum design analysis process.

Assumptions

This study utilizes the following assumptions:

- Students were intrinsically motivated to complete their undergraduate degrees.
- Students were financially responsible for completing their degrees on time.
- Academic programs have a well-defined prerequisite and post-requisite curriculum flowcharts.
- ACR system was developed based on network analysis and institutional data analyses. It is important to note that ACR recommendations are not based on any person's personal opinions about courses and curriculum.

Analysis and Results

As mentioned previously, the development of the Adaptive Curriculum Refinement system consists of two major components: (a) intuitive data visualization to understand student degree mobility patterns and (b) network analysis of courses to study program curriculum. The intuitive data visualizations to understand student degree mobility patterns were illustrated under the description of Research Question 1 in Chapter Four (refer to Research Question 1: Impact of Traditional Program Curriculum on Student Success). Another component, "network analysis of courses," to study program curriculum was explained under the description of Research Question 2 in Chapter Five. This chapter used variables stated in Table 1.

Development of ACR for Computer Science Program

First, the average number of times taken by each student was calculated for all courses in the curriculum. Second, the risk factor was calculated for every course. The descending order of risk factors for CS courses is shown in Figure 16. The average risk factor Avg_{Rf} for CS courses is 1.63.

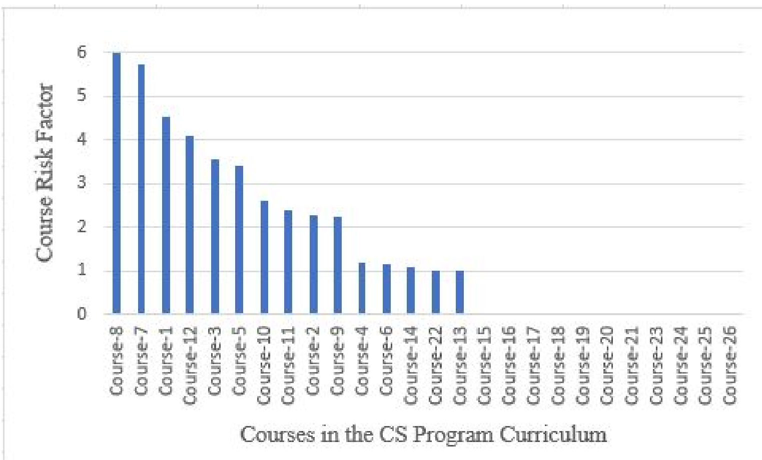
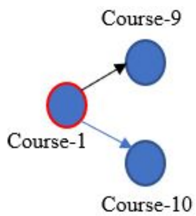
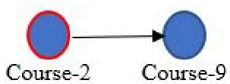
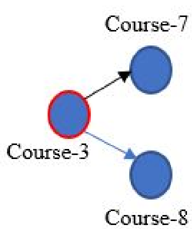
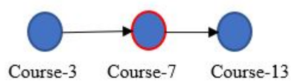
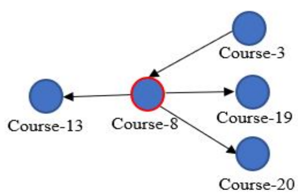
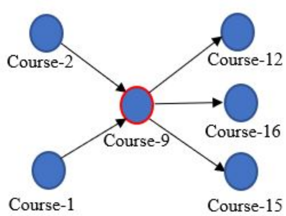
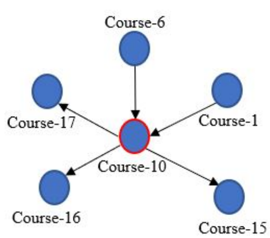
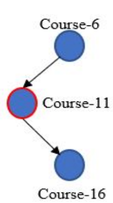


Figure 16: CS courses and their risk factors.

Third, a set of courses that have a risk factor value greater than 1.63 were selected. Courses such as course-1, course-2, course-3, course-5, course-7, course-8, course-9, course-10, course-11, and course-12 had values greater than 1.63. Each of these courses was examined with respect to their prerequisites and post-requisites (see Table 19). Courses with any two of their post-requisites having course c_i as a prerequisite were selected. For example, course-3 has two post-requisites: course-7 and course-8. These two courses only have course-3 as their prerequisites. Students' time to graduation can be reduced if course-7 and course-8 were made co-requisites.

Table 19: Prerequisite and Post-requisite Analysis of CS Courses

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-1  	2	4	N
Course-2  	1	2	N
Course-3  	2	1	Y
Course-5  	0	NA	NA

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-7 	2	2	N
Course-8 	4	4	N
Course-9 	5	7	N
Course-10 	5	7	N
Course-11 	2	3	N

The number of terms provided in the current program of study (11 terms) is illustrated in Table 20. The number of terms required for CS students to complete all courses in the program curriculum if course-7 and course-8 were made corequisites was eight (see Table 21).

Table 20: CS Program Plan of Study

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7	Term-8
Course-1	Course-5	Course-12	Course-11	Course-22	Course-16	Course-19	Course-25
Course-10	Course-3	Course-6	Course-7		Course-17	Course-24	Course-20
	Course-9		Course-14		Course-18		
	Course-8				Course-15		

Term-9	Term-10	Term-11	
Course-23	Course-13	Course-26	Course-21

Note. Course-2 and Course-4 are high school level math courses and were not included in the plan of study.

Table 21: CS Plan of Study if Course-7 and Course-8 were Made Co-Requisites

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7	Term-8
Course-1	Course-3	Course-7	Course-9	Course-14	Course-11	Course-13	Course-20
Course-10	Course-5	Course-8	Course-15	Course-19	Course-17	Course-16	Course-26
	Course-6		Course-18	Course-23		Course-21	
	Course-12		Course-22	Course-24		Course-25	

Note. Course-2 and Course-4 are high school level math courses and were not included in the plan of study.

Development of ACR for Computer Engineering Program

The average risk factor Avg_{Rf} for CE courses is 1.61. Courses such as course-1, course-2, course-3, course-4, course-5, course-6, course-7, course-8, course-9, course-11, course-18, and course-20 had risk factors greater than 1.61. The course risk factor values of CE courses are shown in Figure 17.

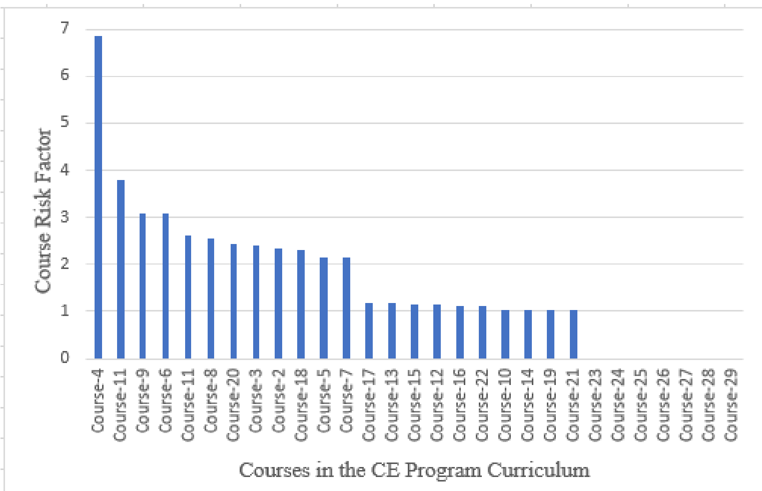
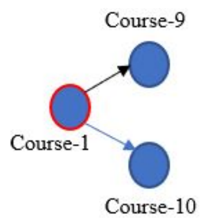
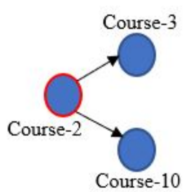
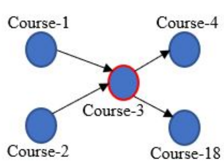
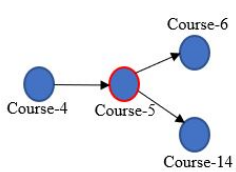
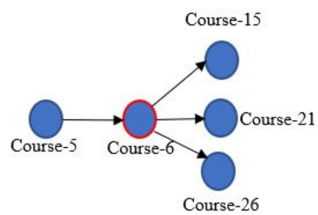
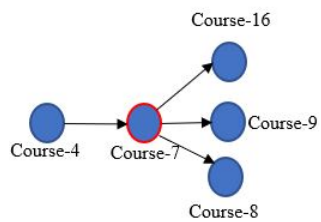
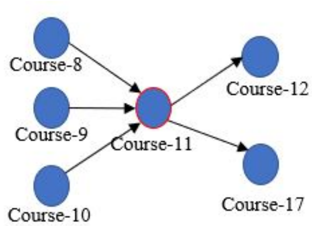


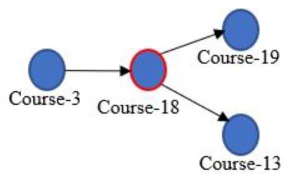
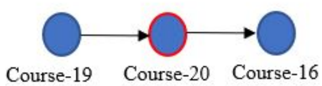
Figure 17: Course risk factor values of CE courses.

The analysis of prerequisite and post-requisites of these courses is shown in Table 22.

Table 22: Prerequisite and Post-requisite Analysis of CE Courses

<table>
<tr><th>Course</th><th>Total Number of Prerequisites (PR) & Post-requisites (POR)</th><th>Indegree number of PR and POR</th><th>Any two Post-requisites (POR) POR = 1? Y/N</th></tr>
<tr><td>Course-1
</td><td>2</td><td>3</td><td>N</td></tr>
<tr><td>Course-2
</td><td>2</td><td>4</td><td>N</td></tr>
<tr><td>Course-3
</td><td>4</td><td>1</td><td>Y</td></tr>
<tr><td>Course-4
</td><td>3</td><td>4</td><td>N</td></tr>
</table>

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-6 	4	7	N
Course-7 	4	3	Y
Course-8 	2	4	N
Course-9 	2	4	N
Course-11 	5	4	Y

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-18	3	6	N
			
Course-20	2	4	N
			

As per the current plan of study for CE, the number of terms required to complete courses was nine (see Table 23). Based on prerequisite and post-requisite analysis, the number of terms required to complete courses in the program curriculum was eight if (a) course-8 and course-9, (b) course-4 and course-18, and (c) course-12 and course-17 were made co-requisites (see Table 24). Thus, the number of terms to graduate can be shortened by making the above listed courses as co-requisites.

Table 23: CE Plan of Study

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7	Term-8
Course-3	Course-4	Course-5	Course-6	Course-16	Course-8	Course-11	Course-12
	Course-10	Course-7	Course-20	Course-26	Course-9	Course-22	Course-28
	Course-18	Course-13	Course-21		Course-23	Course-25	
		Course-19	Course-14 or Course-15		Course-27		

Term 9
Course-17
Course-24
Course-29

Note. Course-1 and Course-2 are high school level math courses and were not included in the plan of study.

Table 24: CE Plan of Study if Course-8 and Course-9, Course-4 and Course-18, and Course-12 and Course-17 Were Made Co-Requisites

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7	Term-8
Course-3	Course-4	Course-5	Course-6	Course-8	Course-11	Course-12	Course-24
Course-10	Course-18	Course-7	Course-20	Course-9	Course-22	Course-17	Course-29
		Course-13	Course-21	Course-16	Course-23	Course-25	
		Course-19	Course-14 or Course-15	Course-26	Course-27	Course-28	

Note. Course-1 and Course-2 are high school level math courses and were not included in the plan of study.

Development of ACR for Information Technology

The average risk factor Avg_{Rf} for IT courses is 1.16. The risk factor values of courses such as course-1, course-2, course-4, course-9, course-10, course-15, and course-17 are greater than Avg_{Rf}.

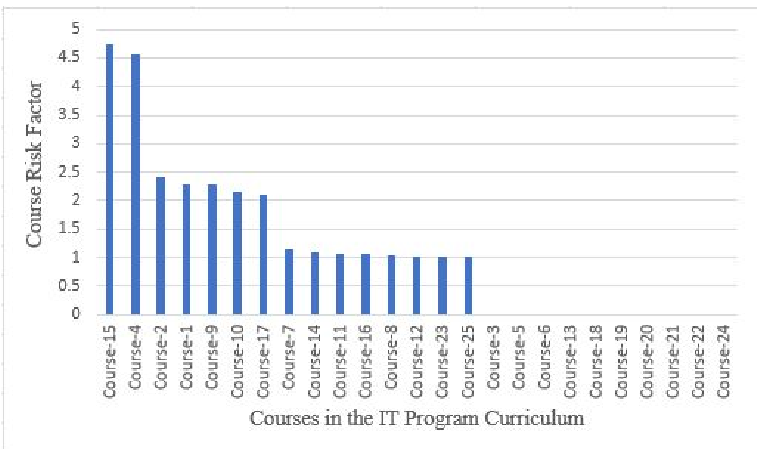
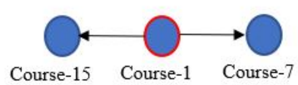
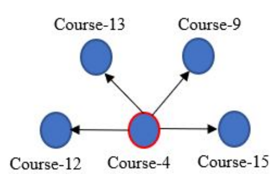
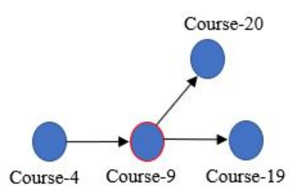
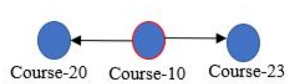
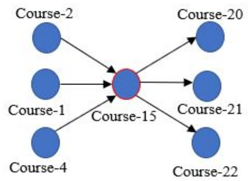
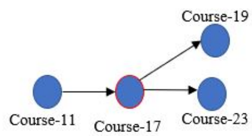


Figure 18: Risk factor values of IT courses.

The prerequisite and post requisite analysis of IT courses as outlined in the algorithm for the development of ACR system is shown in Table 25.

Table 25: Prerequisites and Post-requisite Analysis of IT Courses

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-1 	2	5	N
Course-2 	2	5	N
Course-4 	4	7	Y
Course-9 	3	6	N
Course-10 	2	7	N

Course	Total Number of Prerequisites (PR) & Post-requisites (POR)	Indegree number of PR and POR	Any two Post-requisites (POR) POR = 1? Y/N
Course-15 	6	6	N
Course-17 	3	6	N

As per the IT program's plan of study, a minimum of eight terms is required for students to complete courses in the curriculum (see Table 26), whereas students can complete all courses in the program curriculum within seven terms if course-9 and course-13 were made co-requisites (see Table 27).

Table 26: IT Program Plan of Study

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7	Term-8
Course-1	Course-2	Course-7	Course-3	Course-11	Course-16	Course-19	Course-20
Course-4	Course-5	Course-8	Course-12	Course-13	Course-18	Course-23	Course-24
	Course-6	Course-9	Course-14	Course-17	Course-21	Course-25	
	Course-15	Course-10		Course-22			

Table 27: IT Plan of Study if Course-9 and Course-13 Were Made Co-Requisites

Term-1	Term-2	Term-3	Term-4	Term-5	Term-6	Term-7
Course-1	Course-9	Course-7	Course-11	Course-3	Course-5	Course-24
Course-4	Course-10	Course-15	Course-14	Course-6	Course-19	
Course-8	Course-12	Course-21	Course-18	Course-17	Course-23	
Course-16	Course-13	Course-22	Course-25	Course-20		

Comparison of Plan of Study and ACR's Corequisite Suggestions in Terms of Time to Complete Courses in the Program Curricula

The number of terms to complete all courses listed in the curricula of CS, CE, and IT as per their plan of study were eleven, nine, and eight terms, respectively, whereas the outputs of ACR system suggest that the time to complete courses can be reduced by considering the corequisite suggestions provided by the ACR system (see Table 28).

Table 28: Comparison of Plan of Study and ACR's Corequisite Suggestions (Number of Terms to Complete Courses)

Program	Number of terms to complete courses in the program curricula	
	As per Plan of Study	As per ACR System Output
CS	11	8
CE	9	8
IT	8	7

Summary

The goal of developing an adaptive curriculum refinement system was to optimize students' time to graduation. The first component in the development process was to understand the degree mobility patterns of students, especially the number of students who dropped out and their course performances. The courses the students failed had high values of risk factor and were individually analyzed in regard to prerequisites and post-requisites. Based on the analyses, the data-driven curriculum has been developed by implementing new co-requisite requirements in the curriculum. Then the newly developed data-driven curriculum was compared with the program of study in regard to the number of terms to complete courses in the program curriculum. The results show that the data-driven curriculum approach tends to reduce the time to graduation of students in CS, IT, and CE programs. Thus, the data-driven approach to curriculum reform helps reduce the time to graduation.

CHAPTER SEVEN: SUMMARY AND DISCUSSION

This study was designed to investigate the relationship between traditional program curricula and student success of undergraduate students at a large public university located in the Southeast. This study was quantitative in nature and utilized institutional data involving student records.

Summary of the Results

As mentioned in Chapter Three, the study utilized institutional level data of three computing programs. The results of this study are based on a sample of 494 students. Additional data were analyzed to answer Research Question Two related to a CS program-specific factor.

Impact of Traditional Program Curriculum on Student Success

The first section of the study set out to determine how the traditional program curriculum impacts students' degree mobility in undergraduate computing programs at a large public university. Traditional curricula were likely to affect the degree mobility of both transfer and FTIC students. In other words, the traditional program curricula were likely to affect students' change of major and dropout behaviors. The scale of effect was significantly larger for transfer students compared to FTIC students.

There exist both statistical and structural (or visual) differences between transfer and FTIC students of all three programs in regard to student mobility through the programs. Also, all three program curricula studied have high stringency values, which means there is a high tendency for students in these programs to either drop out or change majors. The CS program was more stringent than the CE and IT programs, which means there is less chance that students who started as CS majors graduate with a CS degree, whereas the chances to graduate in the same major are better for CE and IT majors. One possible future study should examine and compare the degree mobility patterns of CS, IT, and CE students before and after passing major gateway courses.

Identifying Drawbacks of Traditional Program Curriculum

Institutional data were used to understand the impact of traditional program curriculum on various student success metrics such as time to graduation and credit accumulation. Also, the effect of a program-specific factor in the program curriculum on graduation was studied. The study found that the higher the stringency, the longer the time to graduation. The study determined that the majority of computing programs have a highly stringent curriculum, which means students had to satisfy various program requirements (including a program-specific factor in some programs) in terms of courses to graduate. Thus, most computing curricula at the target university are stringent.

Traditional computing curricula of CS, CE, IT were likely to affect students' time to graduation. This is due to many prerequisites and post-requisite requirements of courses in computing programs. The CS program at the target university has a high curriculum stringency value compared to other programs because CS has a program-specific factor. The study determined that having a program-specific factor in the curriculum affects students' time to graduation and the graduation rates.

Another factor, “credit accumulation,” was studied to determine the effect of the traditional curriculum on student graduation. The results show that the curriculum stringency does not significantly affect students’ credit accumulation towards graduation. Students tend to accumulate additional (more) credits than required for graduation irrespective of the curriculum stringency in the case of CS, IT, and CE programs. However, CS students who changed their majors tend to accumulate more credits than the other two programs. This could be due to the presence of a program-specific factor in the program curriculum. CS and IT programs differ in terms of credit accumulation for graduated students. Future research may want to examine the effects of a program-specific factor on course enrollment in courses other than prescribed courses in the curriculum.

Data-Driven Curriculum Development (Adaptive Curriculum Refinement System)

The goal of developing an adaptive curriculum refinement system was to optimize students’ time to graduation. The first component in the development process was to understand the degree mobility patterns of students, especially the number of students who dropped out and their course performances. The courses the students failed had high values of risk factor and were individually analyzed in regard to prerequisites and post-requisites. Based on the analyses, the data-driven curriculum has been developed by implementing new co-requisite requirements in the curriculum. Then the newly developed data-driven curriculum was compared with the program of study in regard to the number of terms to complete courses in the program curriculum. The results show that the data-driven curriculum approach tends to reduce the time to graduation of students in CS, IT, and CE programs. Thus, the data-driven approach to curriculum assessment and reform helps reduce the time to graduation.

Further Considerations of the Research

The overall contribution of the institutional data in the development of data-driven curriculum was impressive in reducing the time to graduation. But there is a need to incorporate "real-time" data of student course performances every term to assess the effectiveness of corequisite and prerequisite requirements. Therefore, additional work should be continued to refine the contribution of the Adaptive Curriculum Refinement system and build the curriculum monitoring system – to help both students and advisors.

Application of Home-Grown Data Analytics over Off-the-Shelf Commercial Analytics

As mentioned in Chapter One, some institutions have been using systems developed by private educational technology companies to monitor students' progress and assess institutional efforts to enhance student success (Blumenstyk, 2014). One of the disadvantages of these systems is that they are not developed to study any institutional factor in depth because of limited software features and access to data. To the best of the researcher's knowledge, there is no specified system to evaluate the program curriculum of an academic program at the target university. In this type of case, home-grown data analytics play a vital role. For example, the graduation rates of the CS program at the targeted university was lower compared to other programs in the same department. The CS department initiated a task to analyze institutional and CS-program level data to determine the institutional factors behind low graduation rates. This effort helped the CS department to take measures based on program-level data analysis to improve the graduation rates of the CS program (Basavaraj et al., 2020). This signifies the importance of having institutional-level data analytics setting in enhancing student success.

Program Curriculum Structure and Student Success

As mentioned in Chapter Two, the program curriculum is one of the institutional factors affecting student success. Based purely on program completion rates of transfer and FTIC students combined, CS and IT and IT and CE programs appeared to demonstrate similar levels of student success, whereas CS and CE appeared to demonstrate different levels. However, the curriculum stringency seemed not to affect the graduation when the completion rates of transfer and FTIC were combinedly considered between CS and IT and IT and CE programs. FTIC and transfer students appeared to demonstrate different levels of student success in all three programs. Even in terms of student turbulence metric values, transfer students tend to experience more distress than FTIC students to complete college. This may be due to various factors.

The curriculum stringency was likely to affect transfer students more than FTIC students. The difference may be due to certain reasons such as (a) transfer students complete some of the courses in their previous college and then transfer them to a new institution. When students transfer, they undergo specific challenges related to adjusting to the new environment (new instruction methods, class size) (Daddona, Mondie-Milner, & Goodson, 2019). The curriculum designers focus mainly on setting requirements for courses, the course outcomes, and setting standards for courses neglecting the characteristics and course proficiencies of specific student groups, including transfer students (Prideaux, 2003).

The program curricula of CS, IT, and CE undergraduate programs at the targeted university are stringent. Some courses have too many prerequisite requirements, and it makes it hard for students to progress in their degree programs. One of the prevalent issues at the targeted university regarding course enrollment was that students could not enroll in high-demand courses (e.g., physics-1 and physics-2) due to limited seats even though they were eligible to take the courses. Also, students in programs that have high curriculum stringency appeared to have a longer time to graduate. Based on these, one might conclude that rigorous curricula affect student time to graduation.

Credit accumulation is a leading indicator that decides students' intention to graduate (Davidson, 2014). The CS, CE, and IT majors who graduated accumulated more credits than required credits. Even though there is no statistical difference between programs in terms of credit accumulation, CS majors who changed their program tend to accumulate more credits than their peers. The extra accumulation was due to the requirement of passing a program-specific factor in addition to passing courses in the curriculum. Studies have reported that students were delaying enrolling in this program-specific factor due to fear of failing, and those who failed this factor took it many times (Basavaraj, Badillo-Urquiola et al., 2018; Basavaraj, Ozmen et al., 2018). Some institutions have the practice of testing students' knowledge in program core areas, which is similar to a course in the curriculum. The study found that students enrolled in an academic program having a program-specific factor tend to have a longer time to graduate. In other words, academic programs with high stringency values are likely to affect students' time to graduation.

Another consequence of having a rigid curriculum was high dropout rates and extensive major-changing behavior. As per Holland (1997), students stay in their program if their academic environment is supportive, encourages their involvement, and aims to increase persistence. However, students leave the program when they feel their program does not support their involvement and persistence, and they start to find a different program within the university where they get the support they need (Reardon & Bullock, 2004). If the curriculum is rigid, then there must be an equally supportive environment for students to be successful as well. However, the support that students get may be very limited in the case of large universities. This could be one of the reasons why students enrolled in programs having a rigorous curriculum tend to drop out and change majors in large numbers.

Some computing programs test students' knowledge in program core areas, redundantly providing too much leniency in their program curricula for students in terms of taking courses not related to their major. In other words, some programs have curricula that focus heavily on testing students' knowledge redundantly (in case of CS), thus neglecting the consequence of students dropping out. This could result in a longer time to graduation or dropout or change of major. Studies have shown that less leniency could hurt the graduation rates of academic programs (Basavaraj, Badillo-Urquiola et al., 2018; Basavaraj, Ozmen et al., 2018). However, even computing programs that do not have program-specific factors (in case of IT and CE) in their curricula tend to neglect some specifics related to student retention in the program and their time to graduation. The results of Research Question 3 show that by reducing the leniency either by making two or more courses to take in the same term (or corequisites) can improve the time to graduation. In this way, the stringent curricula can be made more streamlined for students to progress in their degree programs and later graduate on time.

One of the reasons higher educational institutions fail is due to limited or no support for students in terms of degree and course planning. Some institutions have been using the traditional program of study to help students plan, but the problem is that there is not much evidence on why that works. Studies have shown why those traditional programs of study fail to reduce time to graduation (Akbaş et al., 2015; Basavaraj & Garibay, 2018).

Student success cannot be achieved without the collective efforts of students, faculty, and academic staff. They should work together to improve student success, as stated by Astin (1984). The curriculum designers and administrators should properly dissect institutional data and get feedback from students during the curriculum development or reform process. In addition to collective efforts to improve student success, institutions should work to improve college experiences. Students who had satisfactory college experience tend to graduate at a higher rate compared to those who did not. Studies have shown that the program curriculum can impact their college experience (Akbaş et al., 2015; Tessema, Ready, & Yu, 2012). However, many institutions fail to reform their program curricula due to many institutional challenges, including the resistive nature of administrators and faculty (Logue, 2018).

Application of Network Analytic Metrics in Program Curriculum Assessment and Reform

As mentioned in Chapter Five, studies have used the network analytic metrics to understand the program curriculum (Akbaş et al., 2015; Wigdahl et al., 2014). As per researcher's understanding, some of the issues that arise while evaluating program curriculum are (a) limited or no standard metrics to measure course importance, and compare courses based on their importance; (b) there were no metric to compare program curriculum of two or more programs including academic programs with additional requirements (e.g., qualifying exam). In these kinds of issues, network analytic metrics play a vital role in helping administrators, faculty in making decisions related to programs. Course cruciality is one of the metrics deduced based on curriculum analysis (Wigdahl et al., 2014). Other metrics such as curriculum stringency, and risk factor may also serve as instruments in the curriculum assessment and reform process . Course cruciality metric helps administrators and faculty in deciding what course or set of courses are important to make decisions related to prioritizing course offerings, course support and retention. This metric defines the level of impact each course has on the other courses in the curriculum. For example, if a student fails to pass a course with high cruciality value then that may influence his time to graduation. The curriculum stringency helps to compare curriculum of two or more academic programs including programs having a program-specific factor. This metric is useful to make decisions related to curricular reform based on another program. For example, one of the applications is when program-A's stringency is greater than program-B's (program-A is difficult compared to program-B, and program-B's graduation rate is greater than program-A) then program-B's curriculum can be used as a reference to determine if any changes can be made in program-A's curriculum. The significance of risk factor is to measure the risk levels of each course in the program curriculum and it has applications in taking measures related to providing extra academic support, allocation of teaching assistants to assist students in their courses to reduce the course dropout rates.

Significance of ACR Recommendations

One of the metrics to measure student success is students' time to graduation (Venit, 2019). As per this study, most computing program curricula were stringent, and students in these academic programs take a longer time to graduate. Most academic programs provide a plan of studies to their students for the course and degree planning. These plans of studies provide a blueprint of a list of courses to be taken by students to graduate. But some of the issues with them were (a) too much leniency in terms of taking classes; (b) too many prerequisite requirements for some courses, etc. These issues impact students' time to graduation.

The primary purpose of ACR is to minimize the time to graduation for students who wish to graduate in their primary enrolled academic program. This can be achieved by suggesting students to complete required courses as soon as possible in their college journey by reducing leniency in terms of taking required classes. ACR recommendations might help students to plan and complete required courses in a timely manner. There have been studies in the literature that indicate students persist and graduate if they were able to complete a threshold number of courses (course milestone) during their first two years of college (Moore & Shulock, 2009). This study has shown that ACR recommendations were better than the plan of study suggestions in terms of the number of terms to complete required courses.

Recommendations on Moving Forward

The use of institutional data to develop a data-driven curriculum will have a strong influence on student success in higher education institutions. The researcher urges higher education institutions to make use of institutional data in the development and reformation of program curricula. It is evident that using institutional data in the development and reformation of program curricula will continue to provide insights to improve the academic success of students.

The researcher recommends the following steps be taken to encourage incorporating institutional data in the curriculum reformation.

1. Create equivalency between the curriculum stringency and the institutional/faculty support for students.

This study found that a program with high stringency value tends to have a high dropout and change of major rates. In this case, the institution expects too much from students in terms of program requirements. One of the most reflective recommendations for institutions is to create a balance between the institutional expectations for students in terms of completion of courses and providing the required support for students to complete their courses. Some institutions often expect too much from students to complete all the necessary courses and to pass additional program-specific requirements but fail to provide necessary academic support (such as teaching assistants to clarify their course-related doubts, assessing student performance in courses consistently throughout the semester) for students to reduce course dropout. It is crucial to create equivalency to reduce course dropout rates. There has been much debate on whether faculty who are good at teaching or those who are excellent researchers could impact undergraduate student success primarily in terms of helping students understand their course and providing necessary support to excel in courses. The equivalency can be achieved either (a) by hiring faculty who were proficient in teaching because not all researchers are excellent teachers or (b) maximizing institutional support in terms of allocating resources for departments to improve teaching and learning.

2. Provide academic support for different student types based on their unique characteristics in regard to course completion.

Student mobility turbulence values showed that transfer students progress differently than FTIC students. Transfer students experience higher education differently compared to FTIC students (Guidos & Dooris, 2008; Styron, 2010). The college experience of the previous institution often influences transfer student success at the new institution (Goodman, Schlossberg, & Anderson, 2006), whereas FTIC students are new to college. So, it is imperative to consider their characteristics while developing the curriculum. One way of acknowledging their characteristics is by introducing transfer and FTIC requirements into the program curriculum. Some institutions already have this requirement in their curricula and assessing these requirements might help improve their graduation rates.

3. Academic programs having a program-specific factor need to provide additional support for students to stay in the program and graduate on time.

This study has shown a program with an additional requirement to pass a program-specific factor often puts students at risk of dropping out. One of the programs targeted in this study has this factor in their program curriculum to enhance their program quality. However, this factor tests students' knowledge more than once and often contributes to high dropout and major-changing rates. Based on this study, the researcher recommends programs to either drop program-specific factor from the program curriculum or take measures to reduce the dropout rates.

Implications for Practice

The results of this study may have broad implications for higher education decision-makers, curriculum designers, and students as they focus on improving undergraduate student success. This study provided an initial assessment of the use of institutional data to reform the program curriculum and suggests additional research directions. In this section, we discuss potential organizational and software system extensions that, in our experience would enable our work to be more impactful in practice. The first step includes the development of decision support management within the institution for curricular development and reformation. Second, the development of a “computing curricular analytic tool.”

Development of Decision Support Management Team

The main goal of decision support management is to help make critical institutional decisions using academic analytics. Academic analytics refers to the use of institutional data to assist in decision making in higher education (Goldstein & Katz, 2005). One of the key characteristics of academic analytics studies is having a leadership team committed to data-driven decision making and the administrative staff skilled at analytics (Goldstein & Katz, 2005).

A key component in the development of decision support management to facilitate curriculum development and reformation based on data is a dedicated team of academic experts including:

- Faculty members: Faculty members who teach mandatory courses are needed to ensure that any interventions from the results of this research support students in becoming experts in their areas and support lifelong learning.
- Data analysts, data scientists, and institutional researchers: Staff members like data analysts, data scientists, and institutional researchers who have expertise in data preparation and analysis are crucial in the team. These personnel play a vital role in decision making related to curriculum assessment and reformation.
- Director of Institutional Analytics: The director of institutional analytics coordinates the wide variety of analytic projects within the institution. This person is critical in providing the connections between analytics and campus interventions and feedback on the consequence of interventions.
- Director of Institutional Research: This person is responsible for supervising all institutional research activities, which includes providing information, managing data collection, analysis for institutional planning, and decision making. This person will be crucial in providing data collection and research support related to the curriculum.
- College Dean and department chair: The college dean and department chair will be critical in making decisions regarding policies based on student data and feedback from other personnel.

Development of a "Computing Curricular Analytic Tool"

This research provides an in-depth analysis of how courses in the curriculum and their prerequisite and post-requisite requirements affect undergraduate academic success. The next step is to develop a simple analytic tool (see Figure 19) to (a) track the performance of students in courses having high-risk factors and (b) showing a pictorial view of courses completed, courses to be taken, and their predicted time to graduation.

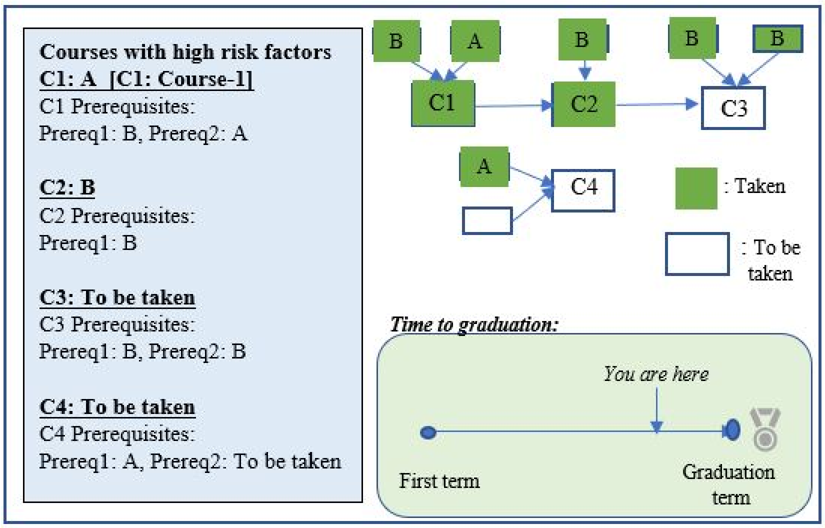


Figure 19: Wireframe of computing curricular analytic tool.

The goal of this tool is to provide a faculty and student with a general idea of how each student is progressing in the academic program in relation to the program curricula.

Implications for Future Research

The results of this study have implications for future research. Future studies might consider extending the Adaptive Curricular Refinement approach for curriculum development and reformation either by utilizing other additional institutional data of student cohorts, including student surveys or by using the output of the system for course predictions. The possible extensions of this study are discussed below.

Additional Student Cohorts

This study utilized the institutional data of a single cohort. Further studies may wish to consider multiple cohorts. Considering multiple cohorts would provide insight into the following questions.

- Do all student cohorts in the same program show similar degree mobility patterns?
- How does the curriculum stringency affect student degree mobility in the case of multiple cohorts?
- Are the student degree mobility patterns in three computing programs considered in this study consistent in other student cohorts?
- The research within this study provides a base for a wide range of data-driven curriculum research to improve undergraduate student success.

Usage of Data-driven Curriculum for Course Predictions

This study utilized institutional data to reform the program curriculum. Future studies may wish to use the result of Research Question 3 for predicting course sequences for students. Future research could examine the following questions:

- Do the course predictions based on a data-driven curriculum contribute less time to graduation?
- What are the differences between the traditional curriculum and data-driven curriculum in regard to course predictions?
- Do course predictions based on data-driven curriculum help improve the graduation rates and time to graduation?

Studying Additional Student Groups

Results from this study were based on transfer and FTIC undergraduate students enrolled in CS, IT, and CE computing programs in a large public university in the Southeast. Future studies should examine institutional data specific to first-generation students. Future research could consider the following research questions:

- How does the degree mobility of first-generation students vary compared to transfer students?
- Does the curricular stringency impact the degree-mobility of first-generation students?
- How does a data-driven curriculum impact the time to graduation of first-generation students?

Conclusions

Higher education institutions become effective when they investigate issues related to critical areas within the institution. Program curriculum is one of the vital institutional factors affecting the students' graduation and time to degree. Program curriculum assessment and reformation processes are complex and expensive tasks for universities. This study attempts to understand how a program curriculum affects graduation and time to degree. Also, this study attempts to make the curriculum reformation process less complex by using curricular analytics and institutional data. This research study provides a base for future studies in the area of curricular assessment and reformation processes, and additional work remains to be explored to develop this research into an adaptable institutional intervention.

Higher education administrators play a vital role in improving student success. Our results highlight the importance of evidence-based decision making across all departments and colleges within the institution to improve undergraduate academic success. This research showcases one way to leverage institutional data to better understand complex, educational, social and organizational issues in higher education.

APPENDIX A: IRB OUTCOME LETTER

Institutional Review Board
FWA00000351
IRB00001138, IRB00012110
Office of Research
12201 Research Parkway
Orlando, FL 32826-3246

UNIVERSITY OF CENTRAL FLORIDA

Memorandum

To: Prateek Basavaraj

From: UCF Institutional Review Board (IRB)

CC: Ivan Garibay
Barbara Fritzsche
Wendy Cartier

Date: April 14, 2020

Re: Request for IRB Determination for Dissertation: *UTILIZING INSTITUTIONAL DATA FOR CURRICULUM ENHANCEMENT TO IMPROVE STUDENT SUCCESS IN UNDERGRADUATE COMPUTING PROGRAMS*

Thank you for contacting the IRB office regarding documentation of IRB review for your study. As you know, the IRB cannot provide an official determination letter for your research because it was not submitted into our electronic submission system prior to the research activities beginning.

However, if you had completed a Huron submission, the IRB could make one of the following research determinations: "Not Human Subjects Research," "Exempt," "Expedited" or "Full Board."

Based on the study information that you emailed the IRB on 4/14/2020, your secondary use of anonymous study data collected from a previously approved protocol, SBE-18-13887: Curriculum Navigator: Leveraging Big Data to Improve Student Success at Four-Year Undergraduate Institutions, would have most likely received an IRB determination of Not Human Subjects Research.

If you have any questions, please contact the UCF IRB irb@ucf.edu.

Sincerely,

Renea Carver

Renea Carver
IRB Manager

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