CRITICAL DIALOGUE ON POLICY AND TRANSFER STUDENT SUCCESS

By

Alyssa Christine Waterson

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Physics—Doctor of Philosophy

2026

ABSTRACT

Every student who enters higher education acquires a different set of experiences than their peers on the way to graduation. Analyzing these experiences is common practice among the fields of Education and Institutional Research, in which the intersection of these practices agree on the need to understand what students are going through in higher education and how to best represent these experiences through success metrics. However, upon identifying groups of students which hold differing experiences and bear unique policies in their higher education pathways, the analysis or success metric choices do not typically change to reflect these unique facets. This dissertation focuses on transfer students who eventually transfer in to MSU and are assessed for graduation-level success metrics such as how long it takes these students to graduate. In challenging the foundations shaping the very success metrics used historically and tied to existing institutional policy, we introduce the concept of data-driven policy work such that practitioners may use their analysis to challenge, inquire about, or iterate on policies relevant to or harmful against student experience.

This dissertation employs various quantitative approaches to exploring this framework of data-driven policy, including descriptive statistics, Analysis of Variance (ANOVA), exploratory Regression techniques, and a dive into Network Analysis. This wide array of approaches aids in framing the exploration of 'data-driven' work. On choosing success metrics to employ these techniques, we first begin by asking whether the metrics we are choosing are appropriate for representing transfer student experiences. For graduation-level metrics, such as time-to-degree, the choice of measuring this particular success metric is first assessed for whether the traditional measurement method reflects attending multiple institutions in higher education. After accessing, acquiring, and curating our data, our chosen analysis techniques help to understand our choices of success metrics for representation of transfer experiences, financial implications, and overall inquiry toward what policy impacts may be present or challenged.

Leveraging these techniques specifically delve through the success metric of time-to-degree in two calculations of calendar time and enrollment time, along with defining and assessing credit loss, excess credit accumulation on graduation, entering credit and course types, and finally the

enrollment prospects of Physics students in a specific window of time. We analyze descriptive statistics for most of these happenings, followed by the more complex analytics for comparisons to First-Time-In-Any-College (FTIAC) students, comparisons across types of transfer students via number of entering credits or other facets of transfer experience, then additionally through the lenses of types of credit loss experienced. This leads to a wide range of exploration for which policies specific to transfer students can be exposed, adding insight to how transfer students navigate our institution *and its system*.

The result of this work aids in reframing how we view policy, specific student interaction with policy, and the idea of data-driven work as a template for improving higher education experiences around policy. Exploring time-to-degree calculations found that transfer students' time in higher education is represented well with a more non-traditional enrollment-based calculation and exposes an interesting facet of credit loss experience, especially in Junior-level entering transfer students attempting to graduate on time or without excess credit. Furthering our work with Network plots representing enrollments in the narrower discipline of Physics showcases the ability to view post-enrollment dynamics transfer students may face and then graduate from under. All of these forward interesting inquiry and how policy is not simply institutional rules, but also exist locally in potential easier-to-reach places for potential research impacts.

Choosing these various lenses and approaches tie together the theme that topics such as policy deserve curiosity, intentionality, and routine inspection for harm or support of students. Policies are the root of institutional experience and, as will be explored in this dissertation, transfer students experience higher education differently from FTIAC students. These different experiences bear implications for and beyond the field of STEM. Practitioners in Education and Institutional Research are introduced to this data-driven framework of research that aims to explicitly support students through higher education.

ACKNOWLEDGMENTS

There are far too many people to thank in a limited amount of space. In my journey at Michigan State University which has spanned more than a decade, I have grown through the people here, the faculty and staff, the classes, the gardens I walked through, the friends I made, the research group I came to know as family, and my new position which has allowed me space to begin my journey in Data Analysis.

My first thanks belongs to Dr. Rachel Henderson. My advisor, my friend, my support, my inspiration. From the moment I met you, I saw a sister in you, as well as much of my research aspirations in you, and much of my humor and qualities of friendship and leadership that I admire and connect with. I fondly recall the time you started at MSU when I was a budding quantitative analyst saying I somehow did a 9-way ANOVA and you said, I don't think that's real?? Who knows, maybe the infamous 9-way ANOVA does exist out there. With you, my research has been able to flourish and expand to fit my interests, my goals, my passions. It has been my highest honor to be advised by you under your guidance and patience, your hardest advice and your kindest critiques. I would not have made it without you. Thank you so much. Now we can go back to being chickens.

My next thanks to my family. My dearest mother, Wendy Waterson who survives my father, Christopher Waterson, who met each other at MSU and passed on the green gene to me. Mom, you are so strong and capable. I learned every bit of my discernment in life from you. I always believed I inherited my strength, my humor, my heart from you. My sister, Sarah Waterson, my favorite person on the planet, the person I've wanted to be since I was conscious (age four? who knows). You see the realest me and have helped me through so much more than just this dissertation. Billy, my misshow is complee <3. My brother, James Waterson, someone who has taught me so much about intelligence, debate, and being articulate and verbose. You are stronger from everything I've seen you face, and you inspire me to grow too; I see much of our father in you, so many great facets of his heart and love for family. And my father, who loved nothing more than his family. I know you're with me, every time I smile, cry, laugh, and dream. I'll see you in the gardens again soon on my next walk.

My dear PERL; my tenure would not be possible without some guy called Dr. Danny Caballero asking if I'd like to LA for P-Cubed back when I was thinking of working at the library. Two years after that, I begged for an opportunity to study abroad and he shipped me off to Oslo, which was a life altering experience. Danny, I grew so much of my knowledge, heart, and humor through you. Dr. Vashti Sawtelle and Dr. Daryl McPadden, I could never have made it here without your guidance, learning from you not just how to be a great teacher and researcher, but also a better person. A literal third of my life has been with this group, this office, these great people. I am preceded by great alumni (Drs. Alanna Pawlak, Abhilash Nair, Kelsey Funkhouser, Mike Obsniuk, Nick Young, Patti Hamerski, Brean Prefontaine, Laura Wood, Carissa Myers, and Cami Monsalve Avendaño) and succeeded by wonderful prospectives that will do great things through and after PERL (Theo Bott, Erin Dachille, Andrea Wooley, Alex Reynolds, Jessi Randolph, Sage Foster, Basma AlMahmood, and John Byrd who has transitioned to CMSE).

Dr. Susan Richter, who I learned so much about confidence in my work and learning how to be a Data Analyst. Thank you for your wisdom and guidance, and for telling me just to get this on paper already! To the rest of my committee, Dr. Joseph Rodriguez and Dr. Lynmarie Posey for taking the time to hear my work out through its wildest stages. To the professors and teachers in my life who made Physics and science fun, I hope you all remember me clawing my way up as much as I remember you giving me the footholds to get here.

My dear friends who heard me complain endlessly at 9 PM about writing my dissertation when they just wanted to game, the Schlansker family (Emily and Katie and sometimes Charlie and Hannah!), my cousin Brian Waterson, and again, my sister.

My dearest and oldest friend Veronica Mendenhall, my sister who will be my family forever. I had you to lean on through so many stages of my life, and the support I have with you and through you will always be treasured so deeply. I've watched you grow so much over this dissertation time period, and I'm proud of who we both have become alongside each other. Love you!!

Sara Uribe, who is one of the absolute kindest people I have ever known, inspired me all the way from middle school and to here to be strong and solid in yourself. As much as I joke around,

please know how deeply I value, respect, and love you and how far we also have come together. No need for a complex <3.

Nicholas Cariello, my best friend and confidant through these tumultuous years. I cannot dedicate enough of this to you who has kept me joyful when I thought I would break. You taught me to shine shamelessly and embrace even more of our humor no matter where we are. Here's to a hundred thousand more hours in Biggby and hoping we win our 50-50s. Love you gworl!!

Emily Carlson and James Coleman (and Yuki and Gia, of course), my life changed forever at orientation of undergrad and has since only matured from knowing you both. You carried my sanity through hard times and I am glad to have you both in my life. Shoutout to the Carlson family as well for many needed getaways!

Jay Hyde, dawg, one of my favorite people on the planet, constantly making me want to move wherever you are just to be closer and geek out 24/7. Thank you for writing with me, resonating shared interests with me, and also carrying my sanity. Love you so much!!

The Gensh crew, of which I promised myself I would not mention *that game* in this dissertation, Dr. Artemis Tsantiri, Lexie Weghorn, and Jazmin Russell (and Nick and James again), y'all are crazy and hilarious and saved my sanity by playing a singular game with me.

Discorders who I met over the pandemic, including the Avecado squad (especially Josh and Jesse) and Ivan Russell. I never thought I would be carried through my early stages of grad school online by such funny and eccentric people. Long live the days of Minecraft, poetry, and lowkey trying to meet up even though none of us have money.

Dr. Carissa Myers, Dr. Camila (Christina Maria) Monsalve Avendaño, Dr. Bryan Stanley, and my dear Andrea Wooley, you all made graduate school so much more fun and bright and gave me ears to complain and joke and be crazy in the office while I put off work. I have dear friends in you all for life, and you all have me whenever you need me.

My dear friends from undergrad, especially Dr. Daniel Oleynik, Dr. Justin Gambrell, and Nat Hawkins who introduced me to Dungeons and Dragons and a hundred great memories of cringe characters we made just to make them all yell at each other.

Thank you to LCC and Envision Green for seeing this work through and hearing me speak its early stages, and to UHW and IR here at MSU taking me up under their wings to be a Data Analyst for them. Thank you all for giving me a chance through and around this work. I have felt so accepted and supported in these spaces. To Dr. Laleah Fernandez, who has the patience of a saint and gave me stunning advice I needed even before she was my primary supervisor. You were right, everything I produced ended up a useful part of the story, even the smallest things.

Shoutouts to my therapist, my dear beloved Mama Kim, my extended family of Watersons and Fairs who supported me and eventually stopped asking when I was graduating (thank you), and the other family and friends I found along the way.

And, to myself, my biggest critic and highest motivator. The only person who told me I could not do this was myself. I realized upon finishing this journey that along the way I said a lot, 'I got this degree out of spite!' but never had someone to stick it to. Turns out that was my own self-doubt. Stick it, me! I did it!

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CHAPTER 1

INTRODUCTION

The introduction chapter will comprise of my broadest communications of each individual topic: Education and Institutional Research, transfer studies, and the shaping of data-driven policy as a conceptual way of thinking through practices in these above areas. As this dissertation is a culmination of years of work through understanding what my work is meant to *do* just as much as what it is meant to *say*, I strive to communicate both impact and meaning of this work from its most scattered beginnings to its cohesive ends.

In my trajectory through transfer student research, I was once inquired about what my research means on many fronts: in the topic of transfer students and 'why I focus on it', in the impacts of policy on students and 'why we should care', and in the space of quantitative methodology and 'how it critiques' experiences of navigating through transfer policy. The philosophical approach of any research endeavor begins with curiosity. Why choose a particular topic? Why is there a reason to care about it? How does it end up mattering after your focus? The inquiry I was faced with directly proceeded a rather lengthy conversation me and my colleague were having about the topic of transfer student success, which I had been coming off of years of general research exploring how long it takes students to graduate. When they asked what does it matter *aside from* my results, my plots, my data, I at last had to face a reality of my work: I lacked a foundation of understanding what my data is *for*.

1.1 Positionality

I ground these topics of chosen topic, care, and critique in my personal experience. I choose this topic of transfer student success, yet I was never actually transfer student. However, I began researching transfer-related data in 2018 with Marcos D. Caballero and John M. Aiken at the University of Oslo, with a sole intent to see if there was interesting data with regard to transfer credit-holding students and 'how long it takes to graduate' [1]. In summation of this time that began my entire graduate school trajectory, I reflect on how this three month period in Oslo allowed me to explore coding, quantitative methodology, and more advanced research projects that lent me the ability to approach transfer student research in a very exploratory and curious manner. Where there was an unfolding interest in this research toward what it means to hold credit and defining what graduation time might mean, there was also a clearly deep rabbit hole in attempting to study transfer students and their experiences.

In Physics Education Research (PER), I have noticed that we often study students with our various methodologies and use this research as a means to critique and improve their experiences in education. The American Physical Society notes that "Research on physics culture, learning environments, and their impacts on students. . . improves our ability to recruit and retain the next generation of physicists", among other notable aims of PER [2]. This particular note is curious, though – one might ask what impacts on students could be measured, which may be thematic of student success; I see questions arise in the latter portion of, what is being done to recruit students currently and... what *is* retention? When we move beyond the idea of simply ‘what is happening currently’, we step outside of the comfort zone of measuring things as we always have done and might instead have something to say about the very definitions of our historic efforts and measurement practices.

Every student has their own unique pathway in education. Often, then, we look at parts of broad student experiences that end up similar. Thus in my time studying transfer students, there are many realms that have unfolded about what it ‘means’ to be a transfer student. It’s not just transfer experiences broadly, it’s *also* that these are STEM students, in Physics curriculum, while viewing these through the lens of interaction with policies implemented in higher education spaces. The unique pathway keeps getting narrower branches, each with their own decisionmaking and navigation principles. Thus, stepping back to the holistic picture of transfer students and framing success through how institutions research these students helps begin the more specific conversations around these narrower branches of experience.

The more meta-question becomes, what do we use this work to say? I bridge this as a mutual understanding of ‘Broader Impacts’ as a concept in tandem with the framework one builds around general research question formation. Broader Impacts are meant to express what your work may impact or, in Layman's terms, what the work is really 'for'. The *framework* situates the work as to *how it should be applied* for this sort of impact. This is especially important in the quantitative methodology realm, as we often represent stories through numbers, plots, and tables, which are susceptible to misinterpretation if not guided by the author's principles, positionality, and results-based discussion. I developed my framework after years of seeing what my work has the potential to impact, and with themes of data-driven policy, it is my hope to show implications about success through Institutional Research practices without yet changing a policy outright.

What this dissertation adds to the PER field is several insights. We study transfer students, especially within Physics students and curriculum requirements, and how understudied and important this research is within our field [3, 4]. We assess policies that transfer students may encounter and the framework by which we can approach quantitatively toward this assessment. We do the work of bridging transfer student experience, policy interaction, and graduation/course-level analytics to view what it means to be a transfer student from multiple lenses. Physics is a rather rigorous discipline that practices problem solving skills as much as mathematic and scientific logic and reasoning, making it somewhat immalleable to curriculum change or additions as highlighted in efforts from Ole Odden and Caballero [5]. The structure of Physics curriculum and navigation through it is strongly impacted by one's starting trajectory in Physics. Holding preexisting credits can be extremely powerful momentum in graduating with a Physics degree; however, *not* holding certain credits in crucial time periods of the pathway may hinder momentum.

I cap my positionality with a reflection on the common inquiry I get each time I present this work: why transfer students? Why care about them specifically? And I used to begin with, "Well, I was never a transfer student, *but*...". I have recently dropped this sentiment altogether and replaced it with, "Why not *choose* to care?" I may be able to frame some of my care around the later sentiments I expressed about the Physics curriculum as a Physics Undergraduate/Graduate alumnus myself. However, I don't want to do that. The positionality of an *Institutional Research practitioner* is to remove the guise of needing passion and instead to implant intentionality. There are far too many lenses our students gaze through at the world of higher education. I cannot experience all of them myself and inspire passion for them. Instead, in the vastness of these experiences, I choose to be curious so that somebody may do the work. I very much enjoy being ‘somebody’.

1.2 Coming to Understand Institutional Policy and Research Philosophies

Institutional policy is an inherent and unavoidable presence when attending an institution of higher education, exemplified through relevant transfer literature [6–9]. While PER is the realm of study encompassing the latter impacts of our results, this dissertation lives comfortably in a broader Institutional Research framework. We will introduce the specific framework in Chapter 2. In this introduction, I recount my positionality in that I am not a transfer student, and thus my personal knowledge of *transfer-based* policy began as a very small list.

The work of Gianna Sorge, Rodashi Roy, and Jazmin Russell, all MSU undergraduates at the time of their work, explored transfer student policies at MSU with intent to give name to many policies, both written and unwritten, and to exemplify what it means for transfer students to navigate these policies [10]. The exploration of these policies shows how extensive the landscape of existing policy actually is, expanding through and far past the likes of limited scholarships, structures to how and how much credit can transfer, and other policies that are a larger conversation of whether they hinder or help these students in their transfer process. Much of the policies we reflect on in this work are geared for transfer students, but in its effect we must work to define and understand what policy is in general.

Institutional policy is the backbone that provides rules, supports, and guidelines for students to follow on their pathway to attaining a degree [6]. Attending an institution of higher education immediately begins interactions with institutional policy through admission principles. What it takes to be admitted is strewn with obvious policies, and transfer students must additionally navigate the intersection of the policies it took to get their existing credits toward the policies it will take at the new institution to keep them. Of course it is easy to say that policies are important to the experience of attending an institution of higher education, but it is less easy to understand what to do about this process when the sentiment as a student seems more and more similar to navigating a mine field.

Before delving into transfer students as a focus in this respect, it is also necessary to introduce the realm of Institutional Research (IR) as a deeply impactful catalyst for this dissertation's formation. In the middle of developing this work, I spent two years as a graduate research assistant with the Institutional Research Office at Michigan State University. This was a position that searched for students interested in working with institutional data and greenlit my pursuit in transfer student research, which was then advised in this time period by Dr. Susan Richter. The perspective of an IR practitioner had interesting overlaps and distinctions from the perspective of Education Research practitioners.

Representing these perspectives as one who at the time was standing in both positions required a philosophical backbone to what each field intends to do with its work. Both fields are able to broach the study of student success, experience, or institutional interaction in their respective, sometimes overlapping, manners. The source of the inquiry is one of several beginnings of the diversion. Education Research exists in multitudes of students' perspectives, seen through the various methodologies of the field such as classroom design, informal and outreach to non-traditional learning spaces, assessment of student success and retention through institutions, programs, and classes, and countless other pursuits [11]. IR is a pursuit dedicated to using an institution's tracked data and analytics to tackle various subjects about the institution's practices, choices, and decisionmaking in future educational pursuits. The methodologies primarily overlap in the quantitative research realm, but the particular choice in research subject can also overlap with regard to assessing student success. It is well within the IR and institutions' general interest to study success realms such as retention, graduation, enrollment, and several other topics that may tap into student 'perspectives'.

My stance through that time ended up on a particular philosophical view: IR considers the institution's perspective in the data they keep and maintain, the questions and standardized metrics they are interested in measuring through, and the very data showcased through certain visualizations and metrics chosen for presentation [12]. Education Research considers *institutional-critical* perspectives in finding and shaping data, inquiry that addresses novel research endeavors, and the means by which they speak to the institution or other audiences about their findings. These were my personal philosophies while sitting in both spaces at once, but I found similar difficulties in addressing institutional policy regardless of either space occupied.

While policy is not inherent to either of these spaces, as it will not shape either narrative developments in every piece produced by either group, the intersection I experienced from being particularly a *quantitative* research practitioner was shaped differently in both spaces. In IR, quantitative practice is extremely common, and though the commonest casual term for them might be practitioners, many are hired as 'Data Scientists' or 'Data Analysts' who perform, specifically, quantitative analyses in their results generation. Outcomes generally align with the typical definitions of success (both in the assessment of enrollees and in the institution's structure), policy, and data needs from the institution, or sometimes held to national standards. Methodology can encapsulate many realms of quantitative or qualitative methods as needed [12].

In PER, quantitative research practice has been a conversation piece expanded upon by researchers such as Lin Ding to move beyond simply performing quantitative analysis for the sake of having data behind a claim, but instead to think more critically about the choice of quantitative methods through purposeful measurement, exploration of relations, and data mining practices [13]. His perspective through these three 'genres' of quantitative work portrays a need to solidify what quantitative methodology within Education Research really adds to the field. Do our measurement, comparison, and data mining choices reflect a purposeful and fruitful study?

My perspective from working on this dissertation is, when we choose a specific measurement, where did it come from and how does it actually look in the IR field, PER field, Education Research field, or in the students' eyes? For example, when we measure time-to-degree, IR has historic institutional perspectives on how it's *been* measured, and quantitative methods might suggest simply choosing a metric and moving along. That is part of the methodological mind-bend; you can do it how it's always been done, or you can stop to question whether historic practices have become stale, obsolete, or in need of new perspectives.

1.3 Policy and Transfer: Why Transfer Students?

We have reflected thus far on institutional policy and transfer student work, beginning with implications that the intersection of these are thematic to this dissertation. However, I want to take this further and entwine these concepts in a new meta-question: why focus on transfer at all? As someone who was never a transfer student, it was stunningly easy to overlook the experiences of transfer students as I began defining them in my initial work. I focused entirely on the type and amounts of credits they attained and pushed that narrative onto how long it takes to graduate. I felt myself, however, playing into the deficit framing that many others have bolstered in transfer work in the past.

What is deficit framing? It's a means of portraying a certain story in a typically negative light [14]. You write your research or results in a way that, for the data or people involved, frames those in a manner that does not encourage their future outlook. In transfer student work, deficit framing litters the narrative with implications that the resulting frustrations & potential 'lack of success' in navigating higher education is an onus put on the student rather than the institutions that ground them [15]. In the navigation of higher education, we as practitioners often measure student success as a post-experience phenomenon: 'How long did it take to graduate?' relies on the student to have completed their pathway entirely, and 'What grades do students get per term?' require finishing those terms. Instead of post-experience measurements, we push to think on the experiences garnered *along* the pathway: 'What helps or hurts time-to-degree?' and 'How does the institution promote safe and welcoming learning spaces?' might be example juxtaposition questions to those posed prior.

Transfer student studies, as we will establish in literature beyond this chapter, become conflated with success measurements while being recognized as a student body that have very unique experiences. Tinto's model of retention is a strong introduction to the connection between transfer experiences and success metrics [16–18]. Retention is measured as the concept of students continually returning to higher education until graduation, often opposed by student drop-out measures. As a tool to try and view retention (or drop-out), Tinto conceptualized this tool as a means of representing what stages students go through navigating higher education up until the ‘drop-out decision’, which *includes* a preliminary stage to recognize their backgrounds and lead-in demographics and experiences as part of this decision [16].

Importantly, in his later works about retention, he has important and relevant takes on actionable items for institutions when success metrics are involved:

> *"Unfortunately too many of our conversations with faculty are not about student education but about student retention. This must change. We must stop talking to faculty about student retention and focus instead on the ways their actions can enhance student education. If faculty attend to that task, increased student retention will follow of its own accord."* (pg. 9).

This quote encapsulates shifting the onus of success away from the student and more toward the *faculty*, but still faces this idea of what we can feasibly *do* when we measure success metrics and find that there are results requiring action or intervention [18]. He specifically calls upon the shift from speaking to these people about retention and instead to address the education by which the students are heralded, as this is one of the core components of his drop-out model: how integrated students feel academically, in their grade performance and intellectual development, can result in decisionmaking about whether or not they want to remain in higher education [16]. But there is no inherent policy that dictates that a ‘student must stay’ for a certain amount of time, and therefore there is no policy that can be developed to specifically target the success of retention. Targeting *faculty* and classroom spaces, again, begins the conversation, but does not entirely face the broad scope of institutional pathways that students hurdle through. In another quote from his 1990 remarks on retention, he speaks more explicitly about the limits of *institutional* action.

> *"There is only so much institutions can or should do to retain all its students. This does not mean that every student does not deserve the same attention and concern regarding his/her education. Quite the contrary. Rather it means that in the normal diversity of students entering most institutions that it is unavoidable that institutions*

will find themselves in the position of eventually encouraging some students to leave while urging others to stay. . . The earlier one addresses the problem of student departure, the greater the likely returns." (pg. 42).

Where Tinto hits on is a recommendation for action that institutions can feasibly target, while emphasizing that institutions cannot stop students from staying or leaving outright [17]. However, later in the work and rounding out the full excerpt, he recommends early intervention. But how early can one intervene with transfer students, let alone any student?

Early intervention is a concept that will be revisited several times through the literature bases forming the data chapters of this dissertation. It forms this narrative that, for any problem occurring down some timeline, there must be a time frame earlier that one can approach the success metric before it is fully shaped into its true outcome. When does a student start thinking about leaving? When does a student actually pause from school and think about coming back? When does a student think about how long it's taking them to graduate and do something about it? There are so many questions about student successes that the student perspective once again becomes entwined with the institution's efforts of broaching said subjects with the students. How early can one feasibly intervene before they are merely directing a student through a pathway they do not want to take?

The transfer experience fits in as a perspective of Tinto's model of retention in a particular interaction with the attributes and pre-institutional shapings that lead in to the full model of dropout. While we discuss in more detail the re-shaping of Tinto's model by other researchers to broach specific demographics of students, it is mostly important to highlight that transfer students are experienced with higher education prior to coming to their destination institution [8, 19, 20]. They have other traits that shape their identity within transfer, such as holding credits that must then be translated to their new institution(s) and they have new degree requirements that might differ from where they were before. In what we see through this work, the experiences transfer students have shifts the very policies they interact with, and therefore the way they interact with the institutions themselves, which rolls through coursetaking decisions, major pathways, and in the end, their targeted success metrics.

There is an additional lens of transfer that matters greatly to the introduction of this defense: that of two-year college transfer students. This is a particular population lens of research and institution bridging that is growing considerably in PER and, as stated before, significantly understudied [21–23]. As noted by Kanim and Cid, PER research subjects are often represented by Calculus-based physics course enrollees (81.9%) where two-year college enrollees in physics hold a menial percentage of the total student population of all the studies comprising their compilation (0.3%); the *actual* populations of these course enrollees are 34% Calculus-based students and 26% from two-year colleges at the time of the study [24]. PER studies of transfer students altogether are extremely limited, and so dialogue typically begins with reports such as from the American Institute of Physics, which provide information about the proportion of Physics students who are two-year transfers and post-graduation outcomes, or survey-based perspectives on supporting transfer through Physics [3, 4].

In part of being understudied, both the small and large perspectives of transfer experiences hold importance to understanding what these students go through on transfer, as both small- and large-scale studies can depict the transfer pathway in impactful and insightful ways. As examples, Wood's narrative on a case-study individual highlights the impact of simply moving from small classrooms to quite large ones in the eyes of a student moving from a community college to a four-year institution [25]. Wang's several studies on transfer provide insight in many realms, but namely her study of 36,618 students to form a cluster analysis and logistic regression on STEM transfer and coursetaking patterns brings a concerted effort to understanding two-year college transfer outcomes in a broad and quantitative manner [26]. These respective studies exemplify different ends of the same branching tree that highlights where transfer-related studies are still growing.

Transfer is not a phenomenon, it is a real, feasible, common option of attending higher education institutions, and as we move into the dissertation formally, the themes we've presented here showcase how I have grown to care about transfer student studies. I do not need to have been one to choose to care. Intentionality is present and possible in both IR and PER practitioners and practices themselves, and bringing together these perspectives through my work shows how transfer students can be studied with curiosity first before assessing their pathways in higher education.

1.4 Structure of Dissertation

This dissertation consists of eight chapters which begin grounding in our focuses on data policy and data-driven efforts around policy, moving through our grounded results and forming ultimate conclusions on what our work is meant to portray in the realms of PER and IR. Our breakdown of chapters is below with brief explanations for their broadstroke supplementary guidance.

Chapter 1 frames the initial conceptions of this work, grounding my personal expertise and previous experience with the goals and intentions of the dissertation's themes. Introducing PER, IR, and transfer student work, we begin to tie in the themes of data-driven policy to segue into the second chapter's deeper dive.

Chapter 2 explains the framework we shaped for this dissertation. Frameworks can be shaped or used as-is from preexisting intellectual works, but ultimately shape foundations for how one's work speaks to the broader world as to the catalyst it will contribute knowledge through. My personally shaped framework is explained and driven as contributory to our fields of knowledge by means of establishing data-driven policy as an important thought tool for future policy critique, change, and creation.

Chapter 3 adds extensive literature backgrounding that is the backbone cover-all literature supporting our data chapters. These chapters are all rooted in transfer-based literature among other themes, which allows our literature review to showcase the extensiveness of transfer research and narrow it inwardly with the themes of data-driven policy.

Chapter 4 is the methodology of this dissertation. Methodology generally encompasses the manner of which the data and results are portrayed, which we will establish continuously through this dissertation as a quantitative endeavor. The research lenses we look through, in both Education and Institutional Research, gives insight to how this data is uniquely structured to match the practice of IR while addressing the questions of Education Research pursuits.

Chapter 5 begins the suite of data presentation through establishing the first approach of the framework: viewing what practices we might employ in measuring transfer success through the graduation-based metric of time-to-degree, then forming dialogue around this metric and its true reach to transfer-based analytics. This chapter approaches this metric as an example of how assessing student data requires a critical eye on who these students are, and therefore how we can use best practices to help measure their successes.

Chapter 6 directly follows the prior chapter in theme and data source, while preceding its place in the framework in more directly facing policies around transferring credit. In the exploration of a phenomenon called credit loss, we are able to expand upon what it means to measure success such as time-to-degree and ground that success metric within active policy impacts. This chapter means to discuss the intersection between what we can measure about students and what those students interacted with to get to the point of measurement of success.

Chapter 7 refocuses data efforts toward new explorations, as it drives new inquiry from what we had explored in the prior two data chapters. In entirely different analysis methodology of Network Analysis, we push the inquiry from in-process transfer to post-transfer inquiry, while narrowing the scope of the prior work from broad institutional descriptive analysis to very local departmental politics and policies. This chapter rounds out the data of the dissertation in showcasing what new inquiry we can explore from our themes and how transfer student analysis can be pushed into many different and interesting realms.

Chapter 8 reflects on the entire dissertation and reiterates the impacts which our efforts bring to the fields of interest, namely within Education and Institutional Research. In summation of the research questions, themes, and framework, we encapsulate what the culmination of the chapters provides in the transfer and policy landscapes. Forwarding our work, we provide recommendations and open letters to future work that branches from these efforts and recognizes what continuing this research may look like and provide locally and institutionally.

CHAPTER 2

DATA DRIVEN POLICY

We began this work on the backbone of Tinto's model of Retention and Drop-out as a motivator for our pursuit of knowledge [16–18]. A *framework* is a concept that follows a similar theme, which I ruminated on for a long time to understand its intention in research. Through an extensive conversation that challenged me on *what my work is meant to do* rather than simply *what my work is measuring*, I ventured away from using Tinto's model as a backbone of anything other than driving inquiry. That is, Tinto's model of Retention and Drop-out is an analytical tool, not a framework. As we introduce my self-curated framework and its development, I offer a guiding definition of frameworks: a framework is the lens by which you look through at and with your work to challenge or add knowledge to the field [27, 28]. Then, it will be important to establish not only the framework itself, but its relation to our work and ultimately the fields it is intended to challenge or add knowledge into.

2.1 Historic Institutional Policy

Institutional policy is interacted with by every student and construes the pathways and barriers they will face as they try to attain their degree. Typically, IR is the means to assess these interactions with that their intent is to view from the institution's view how the students are 'doing'. Their metrics of analysis pertain to the institutional purview of progress, and therefore policy outlines how a student is navigating this space from enrollment to graduation and around those bounds.

Framing policy as historic is not always true. Policy morphs and changes with national standards, the needs of the time, and with who the policymakers are [6]. Indeed, where comes the addition or change of policy is behind it a policymaker; the institution's administration heralds its policy makeup, though sometimes beholden to national standards. For example, any individual institution of higher education might have differing standards for enrollment requirements such as requiring the SAT or ACT, while the mere choices of an SAT or ACT might be a factor of a national standard utilized in this policy choice. However, these choices often *become* historic as they become routine or, in tandem with the concept of aligning with national standards, standardized.

When the policy has worked for a while, or for the majority, it remains often uncontested for years, where then standards become immovable. As O'Conner states in her work on change dynamics in higher education, *"[The] examination of institutional narratives and their relation to broader public discourse allows for some insight into the complex negotiations that institutions are confronting between external influences and internal rationales, and between incremental and disruptive change"* (pg. 633) [29]. It can be said that policies are necessary as guidelines and standards for the institution to adhere to, on principle of what it takes to attend and earn a degree from their institution. However, these guidelines and standards should not be exempt from review, change, or removal if they are found to be harmful or to be acting as barriers for any type of student. With O'Connor's mindset, it is true that change should not be disruptive and might be serviced better incrementally; however, this still requires receptiveness to any change. Our research avenues are then able to act as pressure points for this change.

2.1.1 Research as Interaction with Policy

Education Research and Institutional Research both have the ability to interact with policy. In more plain language stated earlier, there is a difference between works that *incidentally* or *intentionally* discuss policy in their work. Published or unpublished, the purpose of this research in both areas is usually to address interests that are not explicitly about policy. Think on some common topics of IR and Education Research: as examples, analysis of enrollment (institutional or course level), graduation, retention, course development, demographic analysis (by institution-defined categories or other research-based grouping for assessing diversity), and countless other frameworks, methods, or focuses often drive parallel to known policies. Research produces results that then speak to research questions meant to add dialogue about changes or recommendations to the field. As mentioned before, policies are complex in how they can be changed or challenged, especially when they are ingrained at the very highest or broadest institutional level.

Through one of these examples, we might think on the topic of enrollment and research how many students are enrolled at our institution, then ask questions about who was enrolled. The principles of who gets enrolled is decided by the standards of the enrollment process such as requiring test scores and transcripts, but this trickles down from institutional to course level policy; how many Physics majors were admitted? What is the enrollment within the department, and what are the requirements of enrolled majors to graduate? The policies become more local in finer grain assessment. Then, we might have been assessing basic number-of-enrollments or, on a more critical lens, who is being supported in their enrollment process and how. All of it speaks either wittingly or unwittingly to the policies that shape enrollment.

The theme we reach for through this example and soon a more concrete study is that of data-driven policy. Practitioners constantly have their eyes on the institutional landscape and they often speak toward or directly to policy in the work they produce. The explored example, having many potential directions to produce results, provides a backbone to the idea of what is 'data-driven'. In essence, what might we use the data and results produced from research *for*? As we narrow in on that overarching theme of policy, we offer the idea that results and recommendations from research can critique and push for change within policy. Should this interaction actually occur, the change incited in the policy or the addition of new policy might be considered, then, a 'data-driven' decision.

Away from our simulated example, we looked deeply into literature for a concrete example of policy-related research that might align with the definition of 'data-driven policy'. One such example is that of Reverse Credit Transfer (RCT) policy and its active implementation across the United States [9, 30–32]. RCT is a policy being enacted nationally in order to aid transfer students in finishing their Associate's degree, specifically allowing students to confer these degrees from their prior institution if they only had a couple of remaining courses left to finish the degree and finishing these courses at their destination institution [9]. This is a policy that is added to the institutions, both the 'sending' and 'receiving' institution, rather than changing an existing policy. Researchers and practitioners then evaluate the implementation through its effects on transfer student success [30–32]. These specific studies evaluate not just how effective the policy is in attainment of Associate's degrees, but also how the students feel affected by it. Namely, what does conferring an Associate's degree *do* for these students? An institution values the number of Associate's degrees conferred, but a student is concerned with the actual strength utilizing this policy holds for them in their job prospects and professional ambitions [32].

We will not go into further detail on how the policy operates at an individual institutional level, but one other aspect of it that aligns with 'data-driven policy' is not only that it is actively being researched on implementation — it is a policy that was created *after* extensive research and data to lay its foundation and curation of how and why to implement it at all. In a broader scope, this example of a data-driven approach to policy implementation encourages the challenging of historically in-place policies, especially for transfer students. Other policies may have once been data-driven, but are historic enough to challenge and reform inquiry including how students are harmed or helped by them, especially in transfer student studies [33].

This foundation of inquiry generation sparks the continuation of challenging, revising, and creating policy. While RCT is just one example of a policy that transfer students may encounter, other policies are plentiful for assessing and measuring in the practitioner's realm. All policies should be held to the same standard of review and critique, and we should be considering a means to think through how to do this in a meaningful manner.

2.2 Introducing the Framework

Through this realm of inquiry around policy, we find this rhythm of 'data-driven policy' as a desired goal of the approach this dissertation takes. Where once my work sat measuring success metrics for the sake of measurement without acknowledging policy, when faced with a question of '*what does it matter?*' my research immediately sought where my success metrics could reach to make change. In working with IR practices, our metrics employed were increasingly questioned and put in the perspectives of institutions or students: the rules and guidelines known as policies are set in place by the institution, and it is the students' goal to navigate these rules and guidelines until *their* desired outcome is reached. For this reason, that rhythm of 'data-driven policy' took shape.

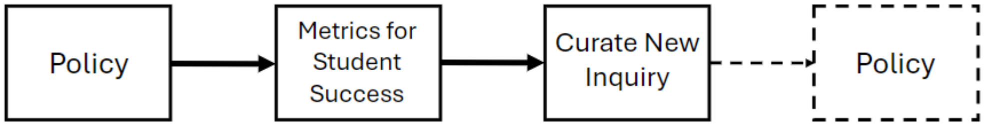


Figure 2.1 The framework of data-driven policy does not have to begin with policy, but should inform and reinform policy from any particular starting point of the journey of analytics. It flows from policy interaction to the metrics used for assessing student success, then to the curation of new inquiry from assessment, and ideally back to the policy or policies interacted with for reassessment.

2.2.1 Concept

Originally, this development was a thinkpiece about how quantitative methodology is generated as a whole in Education Research. I thought of it as a progression of receiving data, asking questions about things you might find interesting about it, and then assessing results/discussion from those questions to bolster new ideas, new changes to implement in your spaces, or further challenge or inspire new research. Where this grew was the introduction of policy as the bridging theme. In quantitative methodology, we might see student data, use our desired success metrics to answer questions about student success, and then generate further inquiry about it. But the data, as we've purported in the above sections, is often ignorantly tied to policy, at least in the way we approach it without so often knowing its ties to our work. If what we intend to pull data for follows policy-related inquiry, followed by using our success metrics to analyze policy (data-wise), followed by generating new inquiry from our results, then this shapes a step-by-step process to tackle a policy. From that, we intend to challenge, inquire about, or iterate on that policy.

2.2.2 Representation

Figure 2.1 shows the framework as we utilize it in this work. Each piece plays its part, including paths one might take through to the next elements. The interpretation displayed shows beginning with a policy (either one you might want to implement or an existing one), then forming connections between that policy and the ways one might analyze it through various metrics for student success to see how students are interacting with the policy, which generates new inquiry from which practitioners might use to go back to the beginning of the cycle and challenge, inquire about, or iterate on the starting policy.

As we established, policies in higher education create a foundation for the rules and guidelines that a student encounters. As students encounter policies, their experiences shift to fit those rules. However, we as practitioners depict the means to evaluate students' interactions with and outcomes from the policy through our defined success metrics. Regardless if this actually cap-ends with having a discussion with policymakers about the policies in question, it bears in mind that students will continue to interact with these policies through time and therefore it is *worth* assessment so that policies do not sit for years uncontested.

The place within this framework that practitioners and researchers might begin in this cycle can vary. The place in the framework one can live in their work can also encompass multiple stages or elements at once, or the flows between. In making this framework, the intent was not to view it as solely a linear and progressive stage-by-stage approach. Research develops often in completely nonlinear fashions. Constructing it this way encompasses a personal desired method for approaching data-driven policy: that *intentional* policy interactions and assessment identifies a policy and discovers its roots, how deep they go, and performs research around what those policies are actually doing to students.

How this dissertation began was more *incidental* than *intentional* in this regard. As my research on time-to-degree has progressed from its inception in my undergraduate work, it allowed for a simpler assessment into a facet of student experience — 'how long it takes transfer students to graduate' — and did not look for a policy at that time in its interactions and measures. As we will explore in the next chapter, transfer students have unique experiences and views, and therefore different policy interactions than non-transfer students. As such, policy became a driver of inquiry and designing this framework. Below, we will to dive further in to the framework piece by piece to understand where practitioners and researchers might typically interact with them and where we intend the framework to steer toward policy critique, change, or implementation.

2.2.2.1 Metrics for Student Success

As we move through this cycle and we keep in mind the overarching theme of 'data-driven policy', one might think it intuitive to begin at the 'Policy' box where we represent the cycle beginning. However, as described before, the framework does not *need* to begin directly assessing or challenging a policy. In fact, the box depicted in Figure 2.1 flowing after 'Policy' is where researchers and practitioners often have their work live within. This is where we begin our framework elements definition.

Metrics for student success show up sometimes mindlessly in quantitative research, such as measuring the time it takes to graduate, retention, or the number of enrollments for the year and leaving those measurements performed as done historically [34–36]. It has been and always will be an important battle figuring out what metrics are relevant, related, or reasonably measurable of our topics. For certain practitioners, being in the midst of regular reporting or even a different type of research question may suddenly show interesting or concerning results about success metrics, then following in broader impact inquiry or generation of new lines of inquiry to explore.

Success metrics keep us oriented toward certain research questions or practices: IR will align with institutional or national standards such that selected success metrics do not waver from these typical practices. Education Researchers might choose metrics more loosely, or rather unbound by expectations of sanitized practices and more into the realm of critique, concern, or creativity. In both realms, we value common definitions and practices, but perhaps do not endorse the measurements settled upon in the same manner or confidence.

The specific focus of policy alongside this box, or more vaguely any overarching topic decided upon by the practitioner, one should consider what their data *and chosen metrics* are curated for. We might have data sitting there, collected for an X purpose and a Y metric of measurement, but *why* did we make those decisions on how that data is put together and measured? Is it simply born from common practice, or was there careful thought into what it means to use that measurement and impose its result across everyone in the dataset?

Metrics help us understand what and how the institution and researchers within care to assess (sometimes continually) of the experiences of students. We can add to this without addressing policy at all. That is, this is the 'practice' part of a practitioner. Even when we consider policy or an overarching topic, though, the metrics of success decided upon don't usually change. That's the problem! Often, our works talk to policy's side rather than its face. Policy, as a part of the system that is difficult to change (as established before), then either is allowed to be upheld or, at best, challenged. ‘Upholding’ the status quo is also a form of indifference. This is where we see much ‘change’ in the form of additional policies and programs, as exemplified by RCT. Later in our Chapter 6, we discuss in literature that many works in the field recommend through their work adding programs, aid, funding, advising, earlier intervention, or other multitudes of approaches that are additional to policy rather than changing that which already exists at its foundation.

So, what can success metrics do for us? We uphold the common metrics and choose to continue measuring without considering why we are choosing *these* measurements. We point at a metric and think, what is the manner in which this is measured or defined, and what are we upholding or being indifferent to in students’ experiences by not stepping outside of the box occasionally? Take retention for example; Tinto’s model was a direct challenging of the perspective of retention and how students might experience it through their pathways in higher education [16]. The consideration of different factors and facets of experiences adds nuance to measuring retention. Our traditional perspectives hold less weight when we are allowed to assess whether people are accurately represented by particular metrics.

2.2.2.2 Curate New Inquiry

The curation of inquiry in this framework is not particularly what forms the research questions for the work in progress, but rather the inquiry that comes through in the development of results or after research has formed its end-level analysis. This mostly forms through the recommendations for future work or, by name, the inquiry that remains after the work has reached its cleaned-up conclusions. Every work has residual questions that could be further explored. This is a piece that often never gets followed up on, as it is the ‘walk’ that comes after the ‘talk’ and requires additional effort or resources to assess.

Why is inquiry important as a whole? It breaks a boundary of what we can or have measured and simply allows us to question what’s going on, and perhaps what to do about it or what might be done to explore further. Maybe chosen practices aren’t ‘good’ or ‘bad’, ‘right’ or ‘wrong’, but perhaps instead what is being told to/recommended to be measured. As quantitative methodology suggests, especially in Education Research as purported by Lin Ding's work, we see inquiry and choose a measure feasible with your data and simply leave it at that [13]. The problem is that in much of research, any residual curiosities or potential branches are left in the shadow of what's *just* been completed because it's the part that is 'next', the part hardest to break through to. What do you do with all these questions you have come up with, or these holes you've uncovered, and these new and interesting problems, what with you just finished one study and now have to pursue another? We live in the comfort of not having to broach the curiosity past mere curiosity.

Our framework then says, what if inquiry can be the part that comes after data *and* we use it from data findings to challenge policy? Inquiry that flows fresh from data and results is also fresh on the topic of policy, as we've just been exposed to what is currently happening and have naturally exposed these noteworthy things in the folds of those findings. In policy, backed by findings, inquiry becomes an absolute powerhouse: what we find through execution of measuring success will have important dialogue on what to do next and how this success is going or has been going for a long time. Without data, we're standing behind policy, more surface level, trying to understand what it even is. Through data, we can see more about not just what it means, but what it does to, or for, students.

2.2.2.3 'Policy' as a Driver

While we did not begin the walkthrough of the cycle elements where it is represented in Figure 2.1, it is true that policy has been thematically present in the other explained elements. The intent of the framework is to address institutional policy, but as well to identify which policy or policies might be the focus. This choice impacts the success metrics we might choose or how those measurements take shape, and then therefore what inquiries might come about. Inquiry after data can challenge institutional policy without limitations, though taking the step back into the realm of the policy we began with becomes that hurdle moment of what we can feasibly do about what we found.

Asking what a policy is leads then into what it is there for. Rather, what does it service, and does it service the institution, or does it service the student? Then, how is it related to a measure or the measure we chose? Policy is not particularly measurable in itself, but students inevitably interact with them, either neutrally/unknowingly, with complication, or as a means of support. ‘Data-driven’ policy follows through us being skeptical of *all* of these potential realms of interaction as to whether the policy is servicing what it was established for. This is where we can make policy that *is* supportive. Inquiry keeps it in check — asking, is this still helpful/hurtful, or what is it helping, or is it in need of updates — then asking for change is less of an adversary when we have data backing us up. Thus we move toward policy that could service both the institution and the students in their goals.

I placed policy at the beginning for a reason. It is the driving beast we mean to confront and, if possible, tackle. I define policy as rules and guidelines also for a reason. Rules and guidelines can and should be checked and rechecked as time and people change. That’s why RCT is a ‘good’ example to begin with, as we see a new data-driven policy establishing its roots and defining its rules and interactions, while still presenting a challenge for what it means to transfer credit and earn an Associate’s degree [9, 32].

Policy can live everywhere from enrollment guidelines to the very end of what it took to confer the degree and formally end higher education. It’s not always a ‘written’ rule, however. There are many policies that are residual from other written ones. For example, while the credit allowed in through transfer is riddled with written policies about what and how much can come in, there are unwritten parts through the process about what the behind-the-scenes decisionmaking is around the translation of credits, at the discretion of a complex amount of sources: the receiving department’s requirements, the university general requirements, pre-existing translation efforts or known course translations, and other nebulous knowledge or confidence about what credits actually come in [7, 33]. Our next chapter will further expand upon this example, but in essence, it is evident what we know and don’t know about policies as soon as they are identified. The purposeful effort of the framework tackling policy for this work is noticing that the concept of “this is how it’s always been done" is not true to a ‘data-driven’ mindset that promotes change and challenge.

2.3 Utilizing the Cycle in Transfer Policy

I go back to the phrasing we used earlier this chapter: that as students encounter policies, their experiences shift to fit those rules. As we will establish in our literature review next chapter, transfer students not only have unique experiences they face in higher education, but also unique policies to interact with. As such, their experience is unique *and* their 'experience shift' through encountering policies is also unique.

Establishing the cycle has already helped us understand that metrics of success break through the veneer of *who* we are measuring and why we seem to often indiscriminately apply our results to a broad scope of students without considering much about who they are. IR at MSU does a great job of showcasing many different student groups, through the institutional or national definitions of how to group them, per their success analytics [37]. It is then also recognized that any IR group or practitioner at another institution is going to adhere to their own institution's practices, and as such, national standards are also rather hard to track when studies branch across multiple institutions. It takes a lot of intentional effort to not only standardize practices, but to be transparent and intentional about your own practices is difficult to approach too. Thus, when we narrow in on transfer policy, our intentionality becomes all the more important.

Facing transfer student research first allows us the question of what transfer student policy there is to work with, or also what policies might differently impact transfer students than others. Being intentional about searching for these policies — such as through the work of the undergraduate students mentioned before who combed hard through MSU's existing policies — allows for assessment of what the transfer landscape of policy actually is and what metrics might help paint the picture of their experiences through it [10]. 'Data-driven policy' only bolsters this potential, as our next exploration of the transfer student landscape will establish how under-researched this landscape truly is, causing any and all inquiry about policy to be highly valuable and thought-provoking.

CHAPTER 3

LITERATURE REVIEW: TRANSFER AND POLICY

In exploring data-driven work, we highlight repeatedly that data-driven *policy* does not always have to be the overarching goal of our framework established in Chapter 2. By addressing policy, we have a target topic that is able to be changed, regardless if that change is difficult or easy to implement. As we explore policy more as an overarching theme, it becomes increasingly evident that policy having a wide array of identities also means that it exists in different forms for different students [6, 38]. This vague encompassment of policy is what it often feels like to address a whole field of experiences at once. Where do you even begin? As it stands, trying to target a massive cloud of experiences and rules and guidelines makes for a behemoth task to find where one's work can make an impact. This dissertation began, however, not as a means of targeting policy at all, but as a way of highlighting what transfer students experience in higher education looks like and how we can measure their successes. As such, this chapter unpacks literature around the transfer student experience and how this naturally guided toward assessing policies that transfer students encounter through their pathways.

3.1 The Transfer Landscape

The starting place of assessing the 'transfer landscape' for this dissertation began first with understanding the success metrics by which we measure transfer student success. The idea of utilizing a measure such as time-to-degree offers immediate questions around its unit of measurement, its typicality of measurement in institutional views, or the end goal of what measuring it might help bring awareness to (e.g. efforts of lowering time-to-degree or increasing retention rates in students) — yet as soon as the scope turns to transfer students' experiences with success metrics, the questions shift to wondering why we might be intentional about measuring transfer students *at all*. The success metric immediately takes a back seat to remark on the choice of the student group of focus, and therefore this literature review begins with the elucidation of transfer student experience research and the historic shift of deficit-based framing to progressive support.

3.1.1 Non-Traditional Students

As stated before, we once explored Tinto's Model of Retention, intending to view its components for relation to transfer student experience [16–18]. On searching for a *transfer student-based* model reflective of Tinto's work, Pascarella *et al.*'s persistence study for two-year college students uses this model through two-year college starters but does not change Tinto's model to reflect any specific experiences of transfer [20]. While this branch of exploration did not bloom, it did unfold an interesting rabbithole toward the identification of 'non-traditional students' in higher education, starting with a piece of literature that *does* shift Tinto's model to shape it differently toward non-traditional student experiences [19]. This work by Bean and Metzner defines non-traditional students through several identifiers, including older, part-time enrolled, and commuting students. Ultimately, what this work supplied was a reformation of Tinto's retention model to better fit *these particular* students. The non-traditional student's (few) named experiences, enough to differ from the 'traditional' student, warranted a different lens to a preexisting line of study, model, or measure.

As one might surmise, identifying the non-traditional from the traditional student is one way of categorizing based off of lived experiences. As we delve further into this distinction, literature aligns the label of non-traditional more explicitly as sharing similar features with transfer students, particularly in Monroe's work which explicitly groups in transfer students in the non-traditional label for her work on attrition [39, 40]. Furthering this, several broader sources provide deeper insight to defining the overlaps that may exist between transfer students and these non-traditional identifiers [41–43]. The Community College Research Center provides detailed information such as what percentage of community college enrollees nationally are working full time during their attendance (46% as of 2019-2020), as well as other general and interesting financial and demographic data [42]. Where the 'non-traditional' student label loosens is that it is never just community college attendees that fulfill these several criteria. As well, as a label, a student may either feel or not feel like a non-traditional student at any point in their trajectory. What we learn from this label is that the overlaps in criteria allow for us to see how our own research fields view, create inquiry around, and present results on these students' experiences and stories.

3.1.2 Deficit Framing

Focusing on transfer students as a potential overlap into the 'non-traditional' student opens tons of perspectives on who transfer students are, where they come from, and why we ultimately research them with purpose and care. The transfer student experience is broad enough to hit a lot of different parts of student experiences: demographic makeup, general population statistics per respective institution of transfer, success analytics such as enrollment or graduation, major trajectories and pathways, and sharper lenses into anecdotal and personal experiences are among the several parts that arise among questions of what transfer students might hold differently than other students [26, 44–58]. Regardless of the literature basis surrounding these potential topics, we must first address a strong issue with much experience-based literature, namely deficit framing and onus of responsibility for support, change, or future work.

Deficit framing in literature generally refers to research framing its subjects in a negative manner or representing the results as the fault or responsibility of those subjects [14]. It sounds extremely negative, as it typically perpetuates harm among those who are affected by this framing, which is especially important that we dismantle its presence with respect to any community researched, for us being transfer students [15]. Intentionality is hard to discern in how research practitioners mean or not mean to cause harm to the people which they are representing in their work. It is crucial, however, to name some bodies of work that help us transition from an older period of research to more modern perspectives of the transfer experience. Perpetuation of certain themes such as comparisons to 'native' students (another term for non-transfer students), concepts like 'transfer shock' or the purported phenomenon of lower GPA on transfer, and implying attending a two-year college generally lowers success in higher education are all a part of this deficit framing and are present in many earlier works [44–46, 51, 59–63].

Added to this perspective is a more recent work by Xu *et al.* which showcases a deep exploration into 'transfer shock' and posing a question of whether transfer students are 'a good bet' for 4-year institutions [51]. This is an excellent transition piece, as in their discussion, there is an explicit lack of onus on the student to address their own barriers, but also circumvents the idea that the community college *alone* must tackle supports for transfer students, as transferring requires both a sending *and receiving* of the student. Amey and Eddy concur this institutional effort on part of promoting partnerships between institutions in how valuable these partnerships could be for community colleges and students who make their way through higher education after high school in general [64]. There are, of course, other supporters of this notion, such as the efforts of the Organization for Physics at Two-Year Colleges and the works of De Leone *et al.* and Savrda *et al.* [22, 23, 65].

3.1.3 Transfer Experience

The experience of being a transfer student can come from a litany of sources, but unfolds most elegantly in closer looks at who they are and how they feel in their transfer processes. There is a bevy literature that does showcase how transfer student experiences are different from First-Time-In-Any-College (FTIAC) students, including work by Yang *et al.* that sought to compare whether the credits transferred in are more applicable for various demographic differences, and whether they count more for their education degree programs, finding that FTIAC students had a higher ratio of applicable transfer credits to the degree program than transfer students had [44–47].

These themes of differences extent out to think on alternate ways to analyze retention, time-to-degree, and graduation, especially in STEM or specific demographic analysis [26, 48–58, 66]. Horn and Skomsvold's work is also an extremely important framing of the transfer experience, compiling around a decade of outcomes for student demographics and enrollment characteristics to describe two-year college students' experiences over time [58]. These outcomes have a wide array of displayed metrics such as students' goals of degree earning, degree attainment, and persistence broken down by several key demographics such as age, race/ethnicity, and other characteristics. Through such a long period of time, we can view success shifts and how each of these demographics might start conversations about who transfer students are and where we see interesting insights from their successes.

As we've seen, breaking down this population by demographics often lends to interesting and key insights to the differences between transfer and FTIAC populations, including those higher in age and, most easily seen in Xu *et al.*'s work, having more historically marginalized students within race/ethnicity demographics [51]. To emphasize this within STEM, as this work eventually narrows down to the Physics curriculum at MSU, focusing on transfer students is an intentional choice in that both their unique experiences and how valuable & diverse these experiences are brings great value for the future success of the STEM field [41, 67, 68]. To put the transfer experience in an even closer view, studies such as Townsend's works show many transfer students expressed they did not want to be treated like new students, but also expressed a desire to be helped along their pathways in a way that is unique to 'new' (FTIAC) students [69, 70]. Laanan *et al.* similarly discuss transfer students' post-transfer adjustment with particular regard to their unique experiences in higher education making their adjustment distinct and interesting [62].

Lastly, highlighting Packard *et al.* in their 2011 work, I was absolutely convinced that the review of transfer student experiences had come full circle; in their work on women who transfer in STEM from community colleges, an academic advisor at the receiving 4-year institution remarks to one of the women in the study, *"You're from Community College, what are you doing here?"* [54]. It was at this point I became entirely convinced that these unique experiences are not only rooted in the mere identity of the transfer student, but in the historic stigma that sprouts from elitism and rejection of community college as a valid path through higher education and the same levels of successes as their peers. This stigma rounds out to those initial noticings of deficit framing and onus of responsibility on the student to help themselves rather than to *be* helped by their host institutions.

3.2 Building Up Transfer Policy Foundations

This dissertation builds explicitly on themes of policy and transfer experience, through each chapter slowly progressing in various success metrics and policies both institutional and local to a more department-level analysis. Policy, as established in the prior chapter, contains an extreme amount of potential avenues to assess. Whether looking at big and broad policies or small and local policies, we want to narrow in with this dissertation at targeting transfer policy and how literature may address the concept of data-driven policy.

Identifying literature in the intersection of policy and transfer is an interesting endeavor, as in many articles, policies targeted from the transfer process are usually adjacently addressed rather than directly and consistently critiqued for change [33, 71–74]. Attewell & Monaghan in their 2016 study do begin with critiquing a policy at their institution in which Pell Recipient status is revoked from students who take less than 30 credits per year [75]. Simultaneously, the authors point out that 'advantaged' and 'academically prepared' students over-represent the population of students taking 15+ credits per semester. Their study displayed that underrepresented (i.e. older, lower average income, non-white, first-generation) transfer students tend to encompass those who take fewer credits per semester, and their results suggest that taking more credits per semester increases their 6 year graduation time. Thus, their recommendation is to take more credits per semester, while recognizing it is a financial barrier to do so for these underrepresented students. This double edged sword presents a 'harm' in that taking fewer credits per semester potentially harmed 6 year graduation outlook, while recognizing that any credit amount under 30 per year rescinds an intensely helpful grant to alleviate that financial barrier.

This brings us to Hodara *et al.* which extensively explore the policies surrounding transferring and translating credit, framing a story around credit loss from these policies [7]. This is a 10-state study in which they explore several aspects of credit attrition, mobility, articulation agreements, and defining institutional policies of these ten states with regard to transferring credit. Hodara *et al.*'s study is the epitome of using research and data to address and critique existing policy, such that part of their recommendations is to 'determine policy effectiveness' through the 'improvement of data systems' and 'research on credit mobility', which follows our framework in its entirety. The study found that credit loss are harsh challenges to transfer students, with recommendations for strong advising and early intervention to identify what pathway students want to take. It marks one of the strongest anchors to data-driven policy as it shapes a feasible policy for tackling, how to dismantle it, and how to recognize when supports are needed and how to provide them from their findings.

Before moving on to an individual-institutional perspective, there are certainly studies that address transfer policy on a more national level aside from Hodara *et al.* [76–78]. The studies by Roska & Keith and Kienzl *et al.* speak to wide national policies around transfer and, in essence, deem the presence of the policies to be intended for efficiency of transfer and altogether quite confusing or ineffective for promoting transfer [76, 77]. Chase *et al.* take these further in a study across seven states for the representation of race/ethnicity considerations within policy, finding that there is little-to-no transfer policy curated around or considering race/ethnicity aside from certain accountability statements adjacent to the policies [78]. The culmination of these studies forms an additional narrative: looking far or close, assessing policy essentially finds a pile of statements, rules, and guidelines that are confusing to navigate or have not been previously assessed for potential harm. Chase *et al.*'s work includes a clause of actually trying to implement policy change, and this implementation of change, rare among the other studies, immediately came across "political constraints" and that "policy change includes persuading multiple stakeholders who often have competing priorities" that the change is necessary and good [78].

3.3 A Quantitative Case Study: Michigan State University

The general evasiveness to tackling policy rounds out just how nebulous even transfer policy itself can be. While Hodara *et al.* and Attewell and Monaghan are able to provide extensive detail on their policies of focus, there are increasing complexities weaved between the lines. We can discuss credits enrolled and transferred, credits lost or financial implications of enrollment, but poking further into *how* credits transfer unfolds a series of additional questions. We can prepare as early as possible, assess financial implications and condense credits as much as possible, but the actual function of transferring and translating credit remains an individual institutional decision. Much like our exploration of Institutional and Education Research earlier in this dissertation, as soon as we delve into extremely specific practices, it becomes more and more evident that we are talking about *Michigan State University* (MSU).

More inwardly, our institution functions with its own policies, influenced nationally or by its peer institutions. Hodara *et al.* emphasize that the state of Texas has over three-thousand existing articulation agreements between its many multitudes of institutions [7]. MSU has its own completely different set of articulation agreements with its own partnering institutions. As practitioners, recognizing a *case study* of occurrences, whether those occurrences are broad or encompassing a large number of students even at a single institution, still represents the experience of transferring within *that* institution. Intentionally addressing transfer student successes and barriers is a more realistic endeavor when we narrow the scope to tackle. As such, as we move into methodology of this dissertation, our work begins with the inspiration of other transfer works both in and out of STEM to shape the case of how MSU's transfer population may be experiencing various lenses of successes.

3.3.1 MSU Transfer Policies

With MSU being somewhat of a 'case study' for analysis, we also recognize our choices in policies of focus might be somewhat local to MSU as well. That is, our transfer students have unique traits of their own, such as transferring more prevalently from *our* top feeder institutions, mostly being in-state transfer students and from two-year colleges. These should not hinder consideration from other institutions on what *their* transfer students may look like and the policies *their* institutions have in place. That being said, we look at a few specific policies in our study that need contextual foundation as we push toward analysis.

One such policy is the 60 credit transfer limit, which we use as both a thinkpiece and heavy focus in Chapters 5 and 6 respectively. Another more local policy or implied set of policies is the consideration of courses required to graduate with a Physics degree at MSU, which we use in Chapter 7 to backbone the conversation of post-transfer dynamics with known course requirements and implied or suggested pathways through those requirements to graduation.

These select policies arose in interest over years of study through coming to understand transfer experiences and shifting the lens to two-year college transfer students. The 60 credit transfer limit policy at MSU is one that on paper only applies to two-year college transfer students, meaning that the other 60 must be fulfilled at MSU. On transfer, their existing credits are assessed for translation, for which this process is more heavily described in Chapter 6. In essence, this specific policy provides a ceiling for which students can exceed credit, but must still earn 60 *more* in order to graduate from MSU, introducing elements of experience such as ‘credit loss’ on entry and intrigue toward how long it takes to graduate or whether excess credits are accumulated by the student on graduation. The more local policy of course enrollments represents a time period in which students are engrossed in their curriculum and, as enrolled in that major, subject to the requirements of graduation within that major, explored thoroughly in Chapter 7.

Our literature rounds back to the value of transfer students in STEM: these are diverse, dedicated students who desire to graduate with a Bachelor’s degree, or higher, and our policies should not be barriers to do so, but rather navigable and true *guidelines* to our success metrics we choose to measure.

CHAPTER 4

METHODS: ACCESSING, ACQUIRING, AND CURATING THE DATASET

Utilizing student data requires a careful process of accessing, acquiring, and curating the source data for a quantitative analysis. This chapter describes the three key elements of forming the dataset used throughout the rest of the dissertation: how we accessed the data, how we acquired and cleaned the data, and then what quantitative methods we used to analyze our data. While student data is broad and encompassing of many aspects of student identity and experience, it is important to note that it is limited to the metrics and standards that are institutionalized or nationalized. For example, tracked demographic variables are often decided by the student's distinction on enrollment and in a multiple choice style that only allows one selection. We ask our readers to keep this in mind as we present our constructed dataset for our analysis.

4.1 Accessing Institutional Data

Within this dissertation, there was a significant amount of time taken to connect with a database that houses all of the student information desired for this and many other projects around student success. In our efforts, we connected with the IR Office and IT Services (ITS) within MSU to collaborate and ensure the security of our connection and data. IR is a group who conducts their own evaluations of educational initiatives which often comprises of using institutional-level data, not limited to student, faculty, and staff data, to represent the institution's progress year-to-year. Some examples are new program efforts, national educational shifts, and other enterprises both in and around the institution. While these evaluations are institutionally important, we had specific interest in the transfer student population at MSU given how large of a population they represent at our institution, more recently between 14-20% of our population [37].

As such, after a year of communicating and negotiating with IR and ITS, we got approval to access the official institutional database called MSUEDW [79]. This database is described therein "*The MSU Enterprise Data Warehouse (MSUEDW) is comprised of the university's central data repositories.*" Within our interests, they include enrollment data, demographic data, college and department-level data, transfer data, and degree information. As a large historic data warehouse, the MSUEDW contains several decades worth of data and are organized as 'schemas'. These schemas are accessed by many different analysis groups on campus and allow for inquiries about institutional data directly to the IR Office.

In addition to student demographics, enrollment, and degree data, the MSUEDW has table views within the schemas that will show the institutions attended by transfer students, the dates that they began and ended at those institutions, and a thorough collection of the credits they have accrued from their prior institutions into what MSU credits these become. However, while the MSUEDW data is extensive, for this study we needed more data encompassing of the transfer experience. As such, we (alongside the IR Office) requested access to data from The National Student Clearinghouse (NSC) [80], a national resource which stores an extensive and historic collection of student data concerning where students have been enrolled at and where they go. The NSC releases regular studies on areas such as student retention, degree attainment, general enrollment statistics, high school benchmarks, and other aspects of the transfer pathway. From this work and collaboration with the IR office, MSU has requested and stored student data from the NSC. The request results in a static file housed by the IR office in a separate schema than most of the other student data. This NSC allows us to view students' term-level information prior to attending MSU. In all, this access process was extensive and concluded over a year of continuous effort, but lays the foundation for which our desired views of transfer student experience is shaped.

4.2 Acquiring Institutional Data

Since the data is housed within the MSUEDW, acquiring data for use in this dissertation required knowledge of *what* is available and necessary for answering our research questions and *how* the MSUEDW stores their schemas of data. For example, degree-level data is present in many tables within the schemas, but there is a view that contains the most specific and thorough information regarding graduation information for each student that has earned a degree from MSU. To help visualize the acquisition of data from the desired schemas, Figure 4.1 shows a general view of the schemas and table views within those schemas considered for joining in the dissertation.

There is a large swath of information and jargon associated with each of the table views, even

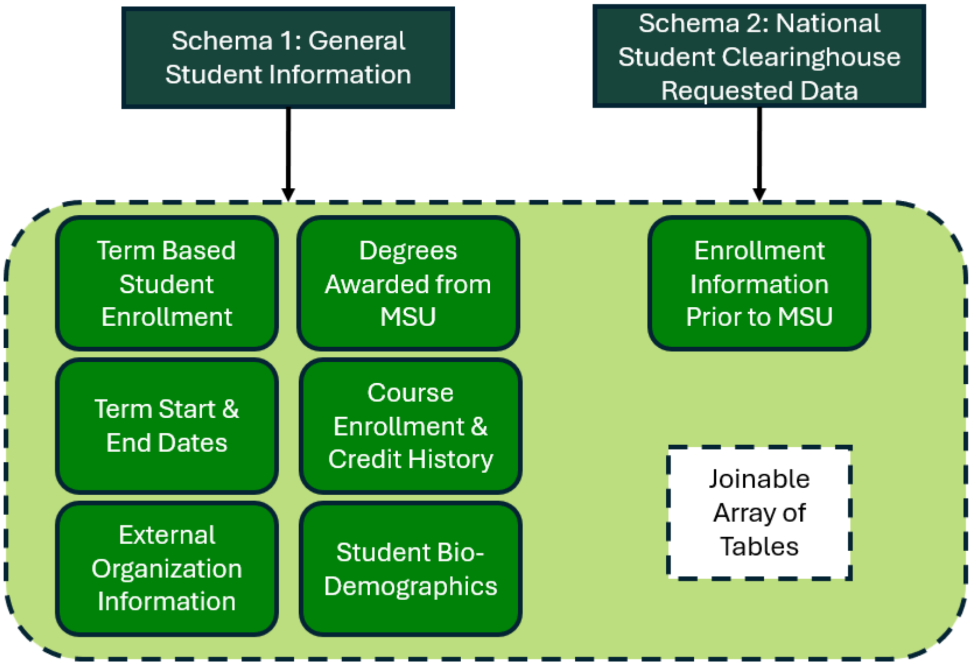


Figure 4.1 Considered schemas and table views within those schemas that contain relevant information about transfer students, each able to be joined into desired datasets.

when we may narrow down to a few considered for analysis. Much of our need for this dissertation is to view student information on a term-based level, such as to represent specific terms enrolled at MSU, as opposed to student bio-demographic information which does not require multiple terms of information to provide details about an individual. Each of these can be selectively or totally joined to represent as much needed data about each student so that there is ample dialogue about transfer student success. After joining, the dataset is ready to be curated to frame the study of interest.

4.3 Curating Institutional Data

We utilized Structured Query Language (SQL) to curate our dataset for which we gathered term-level enrollment data, then degree-level data, demographic data, and prior institution data (see Appendix A for queries). Per query generated, I limited the columns of interest to our research question needs and joined primarily on student ID to retain information per student. Descriptions of these columns can be found in Table 4.1.

With each joining, the dataframe grew to showcase more and more details on term-based enrollment up to graduation, and with NSC data it became clearer within transfer students what

Table View	Column Title	Short Description
Term Based Student Enrollment	- Student ID - Entry Status - Academic Level Status - Cohort - Previous Degrees - Academic Plan	- Unique identifier per student - Identifier which discerns Transfer or Non-Transfer - Current status of credit amount (e.g. Freshman) - Year or Term enrolled first - Highest level of prior degree held - Major per term
Degrees Awarded from MSU	- Completion Term - Academic Plan - Degree Type - Cumulative Graduation Credits	- Coded term on graduation - Major on graduation - Level of degree, e.g. Bachelor's - Number of credits on graduation
Term Start & End Dates	- Term Title - Term Start Date - Term End Date	- Coded term description - Date of term start - Date of term end
Course Enrollment & Credit History	- Course Subject - Course Code - Incoming Transferable Credit - Adjusted Credit	- Subject which describes course department - Code which distinguishes course level - Amount of credit accepted for transfer - Amount of credit adjusted on entry
External Organization Information	- Institution Name - Institution Type - Enrollment Start Date (Per Institution) - Enrollment End Date (Per Institution)	- Name of institution enrolled - Distinction of two-year or four-year institution - Date of first enrollment at institution - Date ended enrollment at institution
Student Bio-Demographics	- Residency - Citizenship	- Tuition code, e.g. In-State tuition - Citizenship type, e.g. International student
Enrollment Information Prior to MSU	- Institution Name - Institution Type - Enrollment Term Start (Per Institution) - Enrollment Term End (Per Institution)	- Name of institution enrolled - Distinction of two-year or four-year institution - Date start of each term enrolled - Date end of each term enrolled

Table 4.1 Various dataset views used or considered in the data pulls of this dissertation, including data from the MSU-Enterprise Data Warehouse and the National Student Clearinghouse. These views are listed alongside commonly used column titles strongly utilized in this work, as well as the datatype of these columns.

shaped their pathways. Seen in Table 4.1, we consider quite a few different types of data to shape our results, including many more columns that we calculated ourselves such as time enrolled or amount of institutions attended. An important distinction of choosing these sources is that there is some repeated information, such as MSU storing its own prior-institution information, then NSC data storing the same data in a more granular, term-based manner.

Each study varies in how many joins occur, though Chapters 5 and 6 share the same primary joining methods and tools, along with outlier removal methods. The specific data curation methods around cleaning data for outliers in Chapters 5 and 6 can be found in Appendix B. Otherwise, the schemas and views chosen for joining can be variant to accommodate the information needed about transfer or FTIAC students, prior institution information, or this wide array of other information available within and around the MSUEDW.

4.3.1 Cleaning Institutional Data

Each final population formation comes from the tables joined together, utilizing custom SQL queries found in Appendix A. Each study's final dataset is described in the subsequent chapters. However, the general population we condense down to comes to:

- Undergraduate students
- Two-Year College (TYC) transfer students*
- In-State transfer students*
- In the (general) range of entry cohorts 2010-2016 (Ch. 5 and Ch. 6)
- Not including times spent dual-enrolled through high school (Ch. 5 and Ch. 6)
- Not including students who have previously earned Bachelor's degrees*
- Sometimes limited to Physics majors or referring specifically to Physics degree earners (Ch. 6 and Ch. 7)
- Sometimes limited to Bachelor's degree earners at MSU (Ch. 5 and Ch. 6)

As Chapters 5 and 6 explicitly share data structures, but Chapter 7 uses a completely unique pull for itself, there are distinct differences in the data curated and available in each chapter. Denoted by asterisks from the above list are points of data that Chapter 7 *can* explore, but we ended up not distinguishing in our results to accommodate the low amount of Physics students and transfer into this major. It also utilizes a cohort year of 2017, which is similarly flexible as an analysis choice. To be clear, the final curation of data for Chapters 5 and 6 explicitly focuses on transfer students that immediately transfer from a two-year college; Chapter 7 follows suit in assessing which of the Physics transfer students come from two- or four-year institutions, but does not omit four-year transfer students. Chapter 7's transfer population is *primarily* two-year college transfer students, however, and thus for the remainder of referring to our data, we will primarily refer to our transfer population as TYC transfer students.

Cleaning data is a particularly important stage for analysis preparation. Analyses depend on consistent and thorough data such that we eliminate as much missingness and 'lack of clarity' from it as possible. The MSUEDW data is well-kept and thorough to the extent that there is virtually no extensive missingness within it, especially in its main term-based view which we utilized extensively. The severest degree of missing data comes from the addition of the NSC data. It requires a specific range of data to request from a list of student IDs, meaning the data would not be expanded continuously beyond what was requested from the NSC. Missingness or inconsistencies in the received dataset mostly amounted to: inconsistent coding of conferred prior degrees (e.g. 'Physics Bachelor's' vs. Physics BA); inconsistent coding of dual enrollment indication; inclusion of MSU as a prior institution depending on program; occasional inconsistent coding of last sequential institution with MSU officially designated the last institution prior to transfer, also potentially program related; missing enrollment times for some institutions attended; overlapping attendance times due to enrollment at multiple institutions; etc. Most of these instances were affecting less than 10% of the remaining population and so were removed entirely, or for the calculation-based cases such as overlapping time, were calculated around so that there was accurate representation of time spent in higher education.

For Chapter 5, there are 7,241 unique TYC transfer students and 33,850 unique First-Time-In-Any-College (FTIAC) students. For Chapter 6, there are 7,229 unique TYC transfer students. For Chapter 7, there are 61 total Junior-level Physics majors enrolled in Academic Year 2017 considered, 24 of which are transfer students and 19 of those 24 transfer directly from two-year colleges.

4.4 Tools and Packages

The programming tools used in this dissertation are: Python, Tableau, Gephi, & R [81–89]. Each of these have their own libraries and packages in consideration for how we specifically analyzed outcomes such as credit loss, time-to-degree, and Network Analysis. The tools and packages individually decide what and how we will shape our data, but always beginning with SQL pulls depicting the individual study's needs. Anecdotally, Python is excellent for shaping data for use in other programs, where Tableau is ideal for single SQL queries that fully builds a 'final' table, and R is excellent for analysis but less efficient with table building. The tools and packages we use have their own pros and cons and 'intended uses' that make choosing them for our study more purposeful or reasonable. Each data chapter will describe the primary tools or packages that aided in forming our results. However, regardless of the study, we will have to clean our data for consistent use.

All data cleaning, dataframe manipulation, and plot representation is performed in Python either through the 'Pandas' [81] or 'matplotlib' [84] libraries. Pandas is extremely proficient in table creation, descriptive statistics, merging and joining, and other data manipulation methods. Pandas in Python was the primary method of cleaning data for both Chapter 5 and Chapter 6, but Chapter 7 had a slightly different data intention which required courses enrolled post-entry at MSU. This also shifted the tools and data construction as outlined above, but mostly was motivated by the statistical methods chosen to address our formed research questions, which will be listed within each study.

4.5 Statistical Methods

Much of this dissertation is performed within the Python platform, as it is versatile and a language worth learning. For most of the curation of plots and tables, I used Python through its various libraries, of course including Pandas, but as well several other libraries in conjunction with their various statistical prowess. We consider 'numpy' [85] a staple, as well as 'scipy.stats' from its main library 'SciPy' [90] and 'scikit-learn' [82]. Each of these performed the main descriptive statistics computation for both Chapter 5 and Chapter 6. Specific choices around what tests are chosen will be described in the methods of their respective chapters; however, below we describe the general use of the chosen statistical analyses throughout the studies.

4.5.1 Hypothesis Testing

Statistical modeling and descriptive statistics were primarily focused on *t*-tests for significance, both related and independent. These utilized the package 'scipy.stats', which uses respective equations for related and independent *t*-tests for our particular population comparisons. This library uses 'numpy' (referred to as 'np' selectively) to perform the *t*-test calculations, which occur as follows:

Related t-test calculation:

$$t = \frac{np.mean(a - b)}{SE}$$

Independent t-test calculation:

$$t = \frac{(np.mean(a) - np.mean(b))}{SE}$$

For both of these equations, a and b are the respective population statistics being measured, where the mean is taken variously between the two t-test equations. SE represents the standard error. Depending if measuring within the same group of students or between different groups of students, the related or independent *t*-test will be applied respectively. This introduces the concept of the Null Hypothesis, which is normally the statement one tries to 'reject' through confidence in the 'difference' between your measurements. As in, the typical use of comparing means or populations is to prove within reason that they are different from each other. This rejects a Null

Hypothesis (H_0) in which it states that the two means have a difference of zero, by then implying the rejection states the two means have a significant non-zero difference from each other. This is supported by a measurement called the $p-value$. This value, in conjunction with a result from a test of significance such as a t-statistic, gives confidence in the rejection of the null hypothesis H_0. The $p-value$ has different intervals which are considered acceptably low enough for sufficient confidence in the rejection. Some fields may require the $p-value$ to be less than perhaps a value of 0.05, 0.01, or 0.001. The $p-value$ can also be conditionally weighted depending on the test executed or population/research question in consideration.

When performing other comparisons such as Analysis of Variance (ANOVA) or Cohen's d effect sizes, the null hypothesis remains largely the same. While these tests are explained in more detail in the respective chapters for which they are used, the H_0 null hypothesis for an ANOVA is largely the same as it utilizes the t-test in its comparison methodology. It simply expands the amount of groups that comparisons are being performed between or within. Cohen's d as an effect size measurement which uses the standard deviation between two means rather than the standard error, and as such the statistic output (akin the t-statistic) 'd' results in the formation of the null hypothesis. If 'd' is non-zero, H_0 can be rejected and, depending on the largeness of the effect size, the difference between means can be determined as small, medium, or large [91].

4.5.2 Regression Modeling

Regression analysis in this study is used as a means of parsing out what variables we might be able to measure about a student, as available in the dataset, and as a means of forwarding dialogue toward the other chapters of this dissertation. We utilize regression techniques, then, through a lens of exploration of what we might be able to infer about each time-to-degree metric as an output variable through various input variables. Linear Regression allows us to predict outcome variables on our individual input variables and represent the predictability of the model.

A typical Linear Regression model is based around the following equation:

$$Y_i = \beta_0 + \beta_1 X_i$$

This shows the dependent variable, or outcome variable, as Y_i as influenced per independent variable X_i. β_0 represents the intercept of the regression, as it ends up a linear-predictive model, and β_1 is the general coefficient of each independent variable X_i.

Test/train splitting is a facet of Regression techniques that prepares some of the data to test on (the smaller portion of the split) and some of the data to train the model on (the larger portion of the split). Typical test/train splits will split the data into ratios like 80% training, 20% testing; in K-Fold techniques, the number of folds serves as the ratio set aside for testing. The designated fold changes each run, to a non-overlapping new piece of the data, until all individual splits are exhausted through the pieces. Then, using 'cross_val_score' and 'cross_validate' (CV) from the 'sklearn' package, we are able to designate the function to produce an *average* R-Squared value from all of the runs [82]. This continues as we add new input variables one at a time, running K times each, averaging the R-Squared values that are outputted. The CV can also be extrapolated for its standard error, which we use to represent errorbars over the R-Squared values, as well as the coefficients (β) from each independent variable of the final model and their respective standard errors after averaging.

4.5.3 Network Analysis

The network plot formation was accomplished entirely through Tableau, R, and Gephi. Our Network research questions were very particular toward the inclusion of physics students and the courses which they are enrolled in at a particular time. With this, data cleaning was very particular toward adding information within the MSUEDW around what courses were once held by transfer students, what those credits were worth, and then what MSU courses those became credit for or what specific worth they were ascribed credit-wise after translation to MSU's standards. Our SQL pull was singular and did not require students who have graduated, and so only pertains to pulling from one view from the MSUEDW.

Utilizing Tableau was a conscious decision regarding a sort of progression toward the typicality of how Institutional Research approaches answering questions similar to ours. Practitioners within the field may be eager to limit tools or programs to the most desired or used tool at the moment.

Tableau is a very popular data visualization tool and has the ability to import data from a source through SQL and format data for usage in other programs, but not as extensively or in a more complex manner than other tools such as Python. For Chapter 7, we needed a tool that could create a Network plot. Python, while versatile in its available libraries for various visualization methods, did not seem the best for performing this visualization. Before the visualization, however, there is still the need to shape the data in the proper format for Network plots, which require information on what data forms nodes and what data forms connections between the nodes, or edges. This is the basis of Network connections: what is being connected and what forms the philosophical basis of the connection drawn? This question is answered in more detail in Chapter 7. The basic requirement for visualization is to get nodes and edges detailed as desired.

After data pulling through Tableau, we took the dataset with anonymized student IDs and the course codes of courses taken at MSU at Junior status enrollment, including the term code and section code which the student was enrolled, and imported these as a Comma-Separated Value document into R [89]. Within R, I use the package titled 'data.table' to format the table necessary for Network Analysis [92]. What this looks like is querying the package to view each student ID and follow the list of course IDs ascribed to the student's repertoire. It outputs the number of attendees for the course ID, then backsources to represent a new table with base student IDs (source), the students that appear in at least one similar course code together (target), then the number of courses connecting the two students (weight). This is then able to be exported as a Comma-Separated Value document once again and utilized in another program or tool.

The tool which we use for visualization of our Network file is Gephi [88]. Gephi is made for showing, editing, and importing/exporting Network plots, and is known particularly for its use in conjunction with other platforms like Tableau. Once importing the file made in R as an 'Edges' file, and an additional file with only identifying/labeling information as a 'Nodes' file, Gephi compiles these together and plots the information as a Network. One can adjust the settings within the plot dynamics to format and make the graph legible, but to the extent it is used in this project is to form where each node and edge will sit on the physical plot. Exporting this information provides a series of X- and Y-coordinates where each node sits and the connections associated with these locations, and these will be exported as a file back into Tableau to perform the last stage of plotting.

CHAPTER 5

CHALLENGING THE TIME-TO-DEGREE METRIC FOR TRANSFER STUDENTS

5.1 Purpose of this Chapter

Institutions utilize a measurement for time-to-degree that represents the total time spent at an institution from the time that a student begins to the time that they graduate. In calculating time-to-degree for transfer students, who attend more than one institution, we should consider this unique experience. As such, we will investigate two types of measurements for time-to-degree that play with the traditional measurement. First considering total time spent in higher education, from enrollment at first institution to graduation at last institution, and second considering a measurement of enrollment time per term enrolled. These calculations show a distinct difference in what is considered to be the total length of time enrolled in higher education. The enrollment time calculation shows less time total in attending higher education while also getting closer to the 4 year graduation expectation, and comparing the calculation types bears implications around transfer policy and financial cost of attendance.

5.2 Introduction

Time-to-degree is a measure of how long it takes students to complete their desired degree in higher education [93]. It is meant to articulate how long one spends in the care of an institution; but considering transfer students, who attend more than one institution of higher education, the traditional lens in which time-to-degree is measured from start to finish may not well represent the nuance of the transfer experience.

Transfer students have a similar demographic outlook to non-traditional students, including potentially being higher in age, having jobs, or having children, as compared to non-transfer students [41–43]. These factors will interact with the time they spent in higher education. As established in the previous chapter, our specific lens of transfer student for this chapter is the population of transfer students whose last institution was indicated to be a two-year college (TYC).

This time is also a financial investment: time-to-degree as a success metric provides insight to financial impacts of pursuing higher education [47, 71, 73, 94]. Studies in graduation metrics such as applicability of credit to the transferring degree and demographic breakdowns (personal or academic demographics) provide more insight into credit articulation and who earns a Bachelor's degree, while bolstering the recognition of unique two-year and community college transfer student experiences within the path of graduation [47, 53, 95]. Insights about transfer experience further develop as we consider the translation process of transferring credits, which is dialogue that we expand upon later in this dissertation. This chapter showcases the time that it takes to graduate, which comprises of time spent at the destination institution and potential time spent at prior institutions. How this time is measured adds a unique perspective to the TYC transfer student experience in higher education in how long it takes to graduate with a Bachelor's degree, which should be an important consideration for the sending and receiving institutions to optimize.

5.3 Refined Background

This section allows us to take a closer glance at literature that may specifically pertain to the time-to-degree metric, general policy argumentation, and financial arguments around TYC transfer student pathways in higher education. This is a more intimate perspective from the broader transfer landscape that was presented in Chapter 3.

5.3.1 The Transfer Experience and Student Success Outcomes

The transfer experience is such that we want to highlight students' non-traditional makeup, their diverse background, and that they tend to be centered in deficit framing literature in that their stories end up steeped in deficit framing rather than promoting themes of success [44–46, 51, 59]. The transfer experience is commonly discussed through the lens of *post-transfer* experiences. It is also discussed *in comparison to* First-Time-In-Any-College (FTIAC) experiences, and especially about how it feels to transfer [45, 51]. The message from literature around the broader transfer experience tells us that it is a) different from FTIAC students and b) different enough to warrant opening cases of alternate ways to analyze retention, time-to-degree, and graduation, especially in STEM or specific demographic analysis [26, 44–46, 48–52, 54–58, 62, 66, 69, 70]. This is further exemplified in Townsend's studies which relay that many TYC transfer students expressed they did not want to be treated like new students, but also expressed a desire to be helped along their pathways in a way that is perhaps in parallel with 'new' students [69, 70].

The transfer experience story with respect to their time-to-degree is more difficult to pinpoint. Transfer time-to-degree is rarely researched [35, 36, 76, 93, 96, 97]. Other 'time-wise' research often diverts to stories of retention in lieu of assessing or challenging time-to-degree [34, 38, 98–102]. Hu *et al.* remark that the field has "yet to empirically examine the time required to earn a baccalaureate degree after enrolling initially at a community college" [101]. These quantitative analytics rarely comment on additional impacts of their research, such as implications toward bettering experiences around transfer retention, finances, and policies or recommendations for doing so.

Total time-to-degree measures one possible end result of transfer: earning a bachelor's degree, post-policy barrier hurdling. Graduation is an outcome, and therefore we can assess it by considering what measurable pieces might be affecting it. The specific method of measuring time-to-degree adds more nuance. An initial perspective from Glass and Bunn discusses the length in years it takes to graduate post-transfer as a calendar measurement, while also including in its survey results the calendar time students may have spent at prior institutions [35]. This is concurred through Gillmore and Hoffman's work in which they curate a graduate efficiency index to measure time-to-degree, which in relation to transfer students, defines time-to-degree as a calendar time from first enrollment to graduation [36].

However, Yue and Fu discuss time-to-degree at much greater length, though not explicitly for transfer students, the *calculation* of time-to-degree around a traditional calendar year versus an enrollment-based calculation, which we consider both in this study [96]. Their research weighs the influence of each calculation type on current studies of time-to-degree and focuses on the enrollment-based calculation for their study rather than comparing the two. We can use it as a stepping stone for more research — if we see interesting results in transfer time-to-degree, we can set the sight for future transfer policy reform, or discuss how to calculate time-to-degree itself. We also see in Cullinane's work that their definition of *transfer* time-to-degree is elapsed terms from first enrollment to graduation, but tends to keep the language around number of terms than years elapsed [103]. This exploration also pushes extensively into the effect of credit loss on time-to-degree, including credit loss and excess credit accumulation, which we will also explore in the next chapter of this dissertation.

As well, the National Student Clearinghouse (NSC) put out an extensive report on time-to-degree utilizing their in-house collected data [93]. This study similarly separates time-to-degree metrics into elapsed and enrolled time, assessing for both Associate's degree earners and Bachelor's degree earners, but not performing statistical comparisons between any particular groups of students such as FTIAC and transfer students. They further identify stop-out time, Associate's degree earning or two-year college attendance, student age, dual enrollment time, and number of institutions as remarkable aspects of transfer student demographics that provide dialogue on time-to-degree. While they do not recommend one metric over the other, they do remark after conclusion that neither of enrollment or elapsed time-to-degree result in 'timely' graduation expectations. As well, they note post-recommendations that public policies affecting both students and institutions may penalize those considered non-traditional, and that recognizing non-traditional pathways leads to better policies and therefore more student success.

5.3.2 Connection to our Data-Driven Policy Framework

We attach this mindset of policy critique to time-to-degree and hit an interesting idea: is time-to-degree a part of an academic policy? While there is no written rule of graduating by a specific time, there are policies adjacent to and involved with the typically anticipated time of a four-year graduation, among policies within transfer pathways such as credit articulation and a 60 credit transfer maximum that we are interested in exploring its interaction with time. Broader literature in the realm of 'policy' and 'transfer' is interesting, as in many articles, 'policies' in the transfer process itself is usually adjacently addressed [33, 71–74]. In this collection, Attewell and Monaghan critique an existing policy at their institution in which Pell Recipient status is revoked from students who take less than 30 credits per year [75]. Simultaneously, the authors point out that 'advantaged' and 'academically prepared' students over-represent the population of students taking 15 or more credits per semester. Their study displayed that underrepresented (i.e. older, lower average income, non-white, first-generation) transfer students tend to encompass those who take fewer credits per semester, and their results suggest that taking more credits per semester increases their 6 year graduation time. Thus, their recommendation is to take more credits per semester, while recognizing it is a financial barrier to do so for these underrepresented students. This double edged sword presents a 'harm' in that taking fewer credits per semester potentially harmed 6 year graduation outlook, while recognizing that any credit amount under 30 per year rescinds an intensely helpful grant to alleviate that financial barrier.

Since this exploration unfolds progressively through this dissertation, the former rounds out the background of *this* time-to-degree study, in that our framework of data-informed policy requires an understanding of the metric by which we measure student success. That is, instead of targeting a specific policy to begin this dissertation, we actually begin in the metrics by which students are held to after (or during) interacting with policy to assess where changing the metric of time-to-degree can challenge the policies adjacent to it.

5.4 Research Questions

To investigate the commonly-used time-to-degree metrics, we pose the following research questions:

1. How do we represent time-to-degree for two-year college transfer students and FTIACs as a metric of student success?

2. How do these time-to-degree metrics differ between two-year college transfer students and FTIAC students?

3. What facets of the transfer student experience are predictive of these time-to-degree metrics?

In approaching the methods, we consider the Research Questions in full. We intend to face questions regarding the metric of time-to-degree and its usage as a representation of student success, which opens questions about how it works as a metric and what aspects of it lend nuance to specific students' experience. Comparing transfer and FTIAC time-to-degree calculations brings forth topics of multi- or single-institutional calculations and whether the enrollment metric is different enough from the calendar metric to warrant choosing the one closer to financial investment in higher education. Connecting back to the framework of this dissertation, we begin analysis in the middle of the conceptualized path through data-driven policy: metrics of student success show through the type of student, the specific metric, and the success being modeled through the metric. Graduation is, as remarked in the literature review, very often measured with graduation rates in focus, then which time-to-degree is kept in a window view of 'acceptable' timing [34, 38, 98–102]. So, extending this to TYC transfer students, we are able to focus on aspects of *being* a transfer student, interacting with policies and programs and pieces of the transfer pathway that are unique to the transfer experience. Outside of basic demographics such as gender or race/ethnicity, there are a litany of facets to transfer students that we can view, and the more we unfold who interacts the most with certain policies, the more we can explore what those interactions may look like, and therefore suggest recommendations for future research both in this dissertation and beyond.

5.5 Refined Methods

Considering the methods of this chapter requires reflection on the finalized population for this study. For this chapter, we narrow down to a population of students with general criteria that was described in Chapter 4.

5.5.1 Sample

We focus on graduating students in order to measure time-to-degree, such that the other limiting criteria are met and we begin this dissertation with 41,101 students, of which 7,241 (17.6%) are TYC transfer students and 33,860 (82.4%) are First-Time-In-Any-College (FTIAC) students. We require this distinction for the purpose of comparing between these groups and their time-to-degree measures when we evaluate through calendar and enrollment times. Through these comparisons, we will also primarily focus on transfer students for the sake of representing statistically significant differences in time-to-degree, and at the end we zoom in on the perspective of Junior level transfer students to round out discussion about what it means to bring in high amounts of transfer credit and assess time-to-degree while interacting with this frame of transfer. The academic-level breakdown of the transfer student population, alongside the total population of FTIAC students, can be seen in

Category of Students	N
Freshman Transfer	1,869
Sophomore Transfer	3,220
Junior Transfer	2,152
Total Transfer	7,241
Total FTIACs	33,860
Grand Total	**41,101**

Table 5.1 Final population of FTIAC students comes to 33,860 after removal of outliers in time-to-degree values at MSU. Final population of transfer students comes to 7,241 students after removal of outliers in time-to-degree values, students who attended more than three prior institutions, and Senior level transfers in low N.

Table 5.1. See Appendix B for information about the application of the 'z-score' method for outlier removal.

Lastly, we have other categories of importance to transfer students that relate to their experiences, but may vary for certain level of entry credit holders than others. We looked in particular at each academic level of entry for what proportion are Associate's degree holders, are transferring directly from our top feeder two-year college, have any non-zero amount of adjusted credit, and have only attended one prior institution. This is viewable in Table 5.2, and will relate variously to our analysis sections within this chapter.

5.5.2 The Traditional Time-to-Degree Metric

The traditional view of time-to-degree at a single institution is the representation of time at the start of enrollment to the time of graduation at that institution. This time calculation is a simple subtraction of dates as follows with MSU as an example:

$$TTD_{Total,Calendar} = Grad_{MSU} - Enrl_{MSU}$$

As we established, transfer students do not only attend one institution. Attending more than one calls into question where the first enrollment date lies, of which we could consider the first institution of higher education that the student enrolled with, or may still consider the enrollment date at MSU and add a certain amount of 'anticipated' years to the students' total TTD amount to

Category	Acad. Level of Entry	% Percent Pop.	N
Associate's Holder	Freshman	0.2%	3
	Sophomore	2.6%	83
	Junior	15.6%	335
	Total	**5.8%**	**421**
From Top Feeder	Freshman	19.9%	373
	Sophomore	33.4%	1,075
	Junior	51.9%	1,117
	Total	**35.4%**	**2,565**
Has Adjusted Credit	Freshman	2.6%	49
	Sophomore	4.0%	128
	Junior	65.2%	1,403
	Total	**21.8%**	**1,580**
1 prior Institution	Freshman	89.2%	1,667
	Sophomore	69.4%	2,234
	Junior	68.7%	1,478
	Total	**74.3%**	**5,379**

Table 5.2 Each subpopulation of interest contains varied amounts of students, with respective proportions per academic level category representing the percent of students within their own group, e.g. of Junior-level transfers, 64.1% have some amount of adjusted credit.

estimate dedicated time in higher education. Our methods will consider answering RQ1 through the introduction of enrollment time-to-degree.

5.6 Analysis Methods

5.6.1 Descriptive Statistics and Hypothesis Testing

In results, we will cover basic descriptions of the differences in these calculations while also providing t-test results for significance in difference between each time-to-degree calculation. The t-test measures the size of the difference relative to the variation in our data. As the t-stastistic raises in magnitude, the null hypothesis can be further rejected, suggesting there is a significant difference in means. Otherwise, if the t-statistic is closer to zero, it gets harder to reject the null hypothesis. It is also commonly associated with a p-value, which is a confidence interval by which one can quickly reference to a given standard (e.g. $\alpha > 0.001$) and bring confidence to state whether the difference is statistically significant. The t-statistic is either performed with 'scipy.stats.ttest_rel' or 'scipy.stats.ttest_ind' in the 'SciPy' package [90]. This is respectively the relative or independent version of the t-statistic calculation, which either compares within a group or between two independent groups.

5.6.2 Analysis of Variance

This chapter specifically refers to the broad population of transfer/FTIAC students primarily and performs a comparison using the Analysis of Variance (ANOVA) method in the specific measurements of time it took to graduate, 'calendar' and 'enrollment' times [91]. These are the same conceptual time (i.e. the time that it takes students to graduate) but measured in two different ways that differ on the choice of scale of measurement, rather than a typical differentiating of measurements such as measuring something at 'Time A' and measuring the same thing at 'Time B'.

What this short example refers to is depicting how we execute the ANOVA, as there are several ways to choose to measure variance in collected data: there are one-way to N-way ANOVA tests depending on how many *factors* are involved in defining the population (from one to N possible ways to split the values), and there are *repeated measure* ANOVAs, wherein the population is either split into groups and compared across groups (no repeating students between the groups) or compared within their groups (the students are being measured for variance among their defined groups).

What remains true for an ANOVA is that there must be at least one Independent Variable and one Dependent Variable, such that there is something to compare across and find a variance in the metric value present between comparison sets. A *factor* is a metric of comparison and one can have more than one factor that depicts multiple comparison groups. Then, there is a decision made around whether the ANOVA is *between* groups or *within* groups. This was described above, and our growing analogy of sampling multiple times from the same group would imply choosing to attempt measuring *within* the groups to find variance among the same people. This then leads to the decision of a typical or a *repeated measure* ANOVA. Even with distinctions like *within* or *between* groups, we still need to tie in the language of *one-way to N-way* ANOVA decisionmaking.

In our expanded analogy, we are measuring within groups for multiple time samples of data, and this means the *repeated measure* is the 'multiple time samples'; if we introduce a *factor*, e.g. transfer/FTIAC status, this would bring our ANOVA to a 'mixed' repeated measures ANOVA, as we are choosing to compare between groups *and* within groups for two different measures. In most cases, choosing to measure *within* groups is a decision that automatically frames the ANOVA as a repeated measures ANOVA, but comparing across groups adds the language of one-way to N-way. Therefore, the mixed ANOVA bridges these languages by performing both between and within to our discretion.

The ANOVA is performed with the 'pingouin' library in Python [86]. It contains functions for all the specified above types of ANOVAs for which we approach comparing time-to-degree outcomes (calendar and enrollment) in our various groupings of students. Each comparison means to challenge whether the times or groups are variant enough to warrant discussion on the preferred choice of time-to-degree metric. Each function runs an eta-squared effect size which, per effect size norm, dictates on a scale of small-to-large the proportion of variance associated with each effect or interaction of effects. This is a calculation based around the sum of squares of the variable over the total sum of squares within the ANOVA model. 'pingouin' provides pairwise t-tests within the particular ran ANOVA, which is the method by which the eta-squared effect sizes between and within groups will be reported. The mixed ANOVA reports on the following: the source of which the comparison is being run (or the interaction of sources, given the mixed model), the degrees of freedom relevant to the number of variables or the number of students in the model, sum of squares (SS) values, means-square (MS) values, F-statistic results, p-values, and a partial eta-squared. The F-statistic is from the F-test, which measures a ratio of variances from the mean. The means-square result is simply the sum of squares divided by the degrees of freedom, and can be useful for potential calculation of the common mean-square error (MSE) statistic. Otherwise, once more we see the p-value providing a quick view of the significance of the comparisons being performed. The partial eta-squared is a value once more attributed to the sum of squares value as follows:

Effect Size	Value
Small	0.01
Medium	0.06
Large	0.14

Table 5.3 Effect size range per eta-squared result minimum comparison, where the value must be met in order to be considered within the Effect Size range.

$$\eta^2, partial = \frac{SS_{effect}}{(SS_{effect} + SS_{error})}$$

This serves as an effect size, wherein the sum of squares for the effect of a variable is put in proportion with the error-sum of squares in the model, then giving a range between 0 and 1 to the proportion of variance in the model that is explained by the current source comparison. The partial eta-square range is seen in Table 5.3.

To report on specific group contrasts that define group or time differences, we utilize the 'pairwise_tests' function within 'pingouin'. There are several statistics reported within this view, but we will focus on the following from the output: the contrast in focus, the time-to-degree type in focus, the group 'A' and group 'B' being individually compared, the means and standard deviations of the groups, the t-statistic reported, the overall p-value, and the eta-squared value. This is not the same as the partial eta-squared value, instead:

$$\eta^2 = \frac{SS_{effect}}{SS_{total}}$$

In this case, the relation is now to the total sum of squares of the model, giving a range of 0 to 1 of the proportion of variance explained by the variable of focus. Comparing two variables, then, we can view the result of this effect size and better determine how much each variable matters with respect to the other considered variables in our time-to-degree outcomes. Classical eta-squared shares the same range of effect sizes as its partial counterpart, referring to Table 5.3.

We have introduced both eta-squared and partial eta-squared as aspects of this analysis; the difference between these measures is a matter of context by which the ANOVA is run and whether there are multiple effects in the model. As explained by Richardson, eta-squared (referred to as classical eta-squared) and partial eta-squared are equivalent if there is only one independent variable associated with the model; on introduction of additional independent variables, a partial eta-squared measurement will ensure that SS_{total} of the ‘current’ independent variable being tested will *not* include a contribution from the SS_{effect} of other independent variable runs of the model *without* the ‘current’ independent variable [104]. In essence, when we compare the difference between time-to-degree metrics later, this is only one independent variable involved, and therefore the classical eta-squared is implemented. As soon as we introduce other factors such as academic level of entry or transfer status as additional independent variables alongside comparing time-to-degree metrics, we use the mixed ANOVA model and partial eta-squared. Since each pairwise t-test runs through individual contrast comparisons, e.g. comparing Junior-level transfer students and FTIACs in enrollment time-to-degree, the ‘pairwise_tests’ function reports classical eta-squared per contrast.

5.6.3 Regression

The main technique we use below is K-Fold cross validation. K-Fold cross validation as an analysis is a means of utilizing a model of your discretion (i.e. Linear Regression) and running it many times in ‘folds’ of itself [83]. For example, using our analysis as a foil, if one does a K-Fold Linear Regression with 10 folds, one would be splitting the dataset into 10 random-but-separable bins, of which one will be considered the test segment, and the other nine will be trained on together. Therefore for the population(s) considered, the students will be randomly split into 10 folds, and then through each of the 10 iterations the ten groups of students switch who is the test fold until all 10 runs complete. You attain 10 total runs of Linear Regression models to average out assessments from each and make your own interpretations of those averages. We chose a split of the data into 80% of it for training and 20% of it for testing in order to predict on the outcome and test its own accuracy. This works for models with plenty of data. We have rather large data considering our time window being 7 years worth of enrollment.

We utilize this method with generating average R-Squared values as our assessment. R-Squared is also known as the coefficient of determination, which ranges from 0 to 1 based on a goodness-of-fit score for the input variables on the outcome variable. If there is no relationship between the inputs and the output, R-Squared is 0. If there is a perfect fit, R-Squared is 1. This range is reminiscent of our earlier depicted eta-squared values, but is now related as the sum of squares' *residual* to the total sum of squares:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

As it was before, the total sum of squares is the distance of the data from the mean, where the residual sum of squares is the distance from the data and the *best fit line* approximation to our data trend.

Recognizing human data as difficult to predict with or on, we do not anticipate the R-Squared value of all of our transfer-related input variables on our time-to-degree outcome(s). Additionally, this is calculated by part of the relationship of all independent variables on the dependent, meaning when one calculates R-Squared for the model, it does not go through each independent variable one at a time and find individual effect on the outcome. Instead, we can view how the model improves by introducing our input variables one at a time, showing the shift in R-Squared each time we run the model K-times. In our model, we run for one input variable 10 times (K-Folded) and take the average of the R-Squared value and its standard error, plotting it. We then run again after adding the next variable in conjunction with the first, running 10 times (K-Folded), and averaging R-Squared until each input variable has been added one-by-one, sequentially.

As we are displaying the average of the R-Squared values, we should also recognize the standard error that may be associated with these runs. Standard error (SE) is calculated as the ratio of the standard deviation (σ) of the values and the square root of the number of samples ($\sqrt{n}$):

$$SE = \frac{\sigma_{R^2}}{\sqrt{n}}$$

As we add input variables into the model, it is noteworthy that we only run for one iteration of adding variables: that is, we are not performing a Hierarchichal model in which we explore all possible combinations of adding our input variables one-by-one. As an exploratory analysis paired with our previous results, we intend to showcase a possible scenario of how to analyze two different time-to-degree outputs using the same Regression method, considering the complexities of human data and identifying transfer-related independent variables. However, the final R-Squared value after adding them all remains the same despite sequence of addition.

As a final representation of our results, we show the average β-coefficients across all runs for all of our models. As introduced in Chapter 4, there is a coefficient for each independent variable, which would be our transfer-related variables, which are in the model to produce the time-to-degree outcomes. The β-coefficient represents the change in the outcome (time-to-degree) per unit of the independent variable (transfer-related variables). It can be positive or negative, which is an indicator to whether the independent variable is positively or negatively correlated to the outcome.

The K-Fold analysis and other regression techniques were executed primarily with the 'Scikit-Learn' package [82]. This contains a litany of functions within Python for statistical and predictive analysis. It utilizes sub-functions from 'numpy' [85], 'SciPy' [81], and 'matplotlib' [84] for calculation and representation of analysis. We utilize 'KFold' and 'cross_val_score' in order to perform the test/train split of our data per the K-Fold designated splitting, and extract additional information such as coefficients using 'cross_validate'.

5.7 Results

5.7.1 RQ1: Representations of the TTD Metric

Time-to-degree is represented in years, for which we utilize the following measurement labels to distinguish: $TTD_{Total,Calendar}$ and $TTD_{Total,Enrollment}$. These encapsulate 'total time' as the idea of all time spent at all attended institutions of higher education, whether it be MSU and all prior institutions for transfer students, or just MSU for our FTIAC students. The total time is then split into a calendar-based calculation or an enrollment-based calculation. Equation (1) describes the total calendar TTD as the first and typical calculation choice.

$$TTD_{Total,Calendar} = Grad_{MSU} - Enrl_{First} (1)$$

This equation shows the difference between the date of graduation $Grad_{MSU}$ and the date of enrollment at the student's first attended institution, $Enrl_{First}$. For a FTIAC student, the first attended institution is MSU, while for transfer students, this is the institution of higher education first ever enrolled. For both types of students we look at the date graduated from MSU.

Enrollment time-to-degree has more complexity given the intent to analyze a metric fitting for total terms enrolled. If we think on the definition, it remains the same for each student type in general: this will be the sum of time through all the terms enrolled at an institution of higher education. We consider the sum of the date-time difference between each attended term in Equation (2):

$$TTD_{Total,Enrollment} = \sum_{i}^{n} \sum_{j}^{m} (Term_{End} - Term_{Begin})_{ij} (2)$$

This is furthered with the representation of this total time as a sum of the term times, where $\sum_i^n$ sums over the first institution i to the last institution n ever attended by the student, and $\sum_j^m$ sums over the first term j to the last term m while enrolled per institution. We can simplify the subtraction of the individual term end and start dates $(Term_{End} - Term_{Begin})$ using a placeholder ε in Equation (3).

$$TTD_{Total,Enrollment} = \sum_{i}^{n} \sum_{j}^{m} \varepsilon_{i,j} (3)$$

This sum, upon expansion, fully fleshes out how many terms a student could be enrolled and where, per Equation (4) showcasing a series of terms at the student's first institution summed with the terms at their second institution, and so on.

$$TTD_{Total,Enrollment} = \varepsilon_{1,1} + \varepsilon_{1,2} + ...\varepsilon_{1,m} + \varepsilon_{2,1} + \varepsilon_{2,2} + ...\varepsilon_{n,m} (4)$$

Again, for FTIAC students, this sum would only include one institution, being MSU; however, transfer students would have $\varepsilon_{i,j}$ variants across multiple institutions. Both student types terminate the sum sequence at $\varepsilon_{n,m}$ at their final term at MSU.

These equations show different ways to interpret time spent in higher education. The difference between these representations of time prior to MSU enrollment is represented as the subtraction of Equation (4) from Equation (1):

$$\Delta TTD = TTD_{Total,Calendar} - TTD_{Total,Enrollment} \quad (5)$$

This equation is used as a comparison in which the resultant numeric value represents potential gaps in education and general time between enrollment. We use this interpretation in our RQ2 and RQ3 results to show where differences between calendar and enrollment time become noticeable, especially if the enrollment time shows a closer representation of the 4-year graduation ‘expectation’.

5.7.2 RQ2: Differences in Metrics between Transfer and FTIAC Students

5.7.2.1 Overall

Representing TTD considers Equations (1) or (4), which we will proceed to refer to the average TTD across our populations in total. On a first pass of this work, we initially considered breaking up these times for transfer students as the time spent prior to MSU and the time spent at MSU, whereas FTIACs only have the latter. This made a first-pass visualization of time-to-degree to show how we might be able to view the differences in time metrics, which we showcase in Figure 5.1.

This initial breakdown in Figure 5.1 shows average times at MSU for FTIACs, which is their total TTD, alongside TYC transfer student times broken down by time prior to MSU and time at MSU, both individually averaged. This initial representation helped to solidify the visual inference of time in higher education with a facet of attending multiple institutions for transfer students, while recognizing that the averages represented for time at MSU encapsulates an average across *all* TYC transfer students. This distinction shows an average of 3.1 calendar years and 2.4 enrollment years of time spent at MSU for these transfer students, which is broadened to each academic level of entry instead of individualized. In general, these averages show that the calendar time spent in higher education is around 4 years for FTIACs but above 5 years for transfer students on average, whereas the enrollment times have clear visual differences, getting smaller by 1 year for FTIACs and by 1.6 years for transfer students total. For FTIAC students, the difference in their time-to-degree metrics

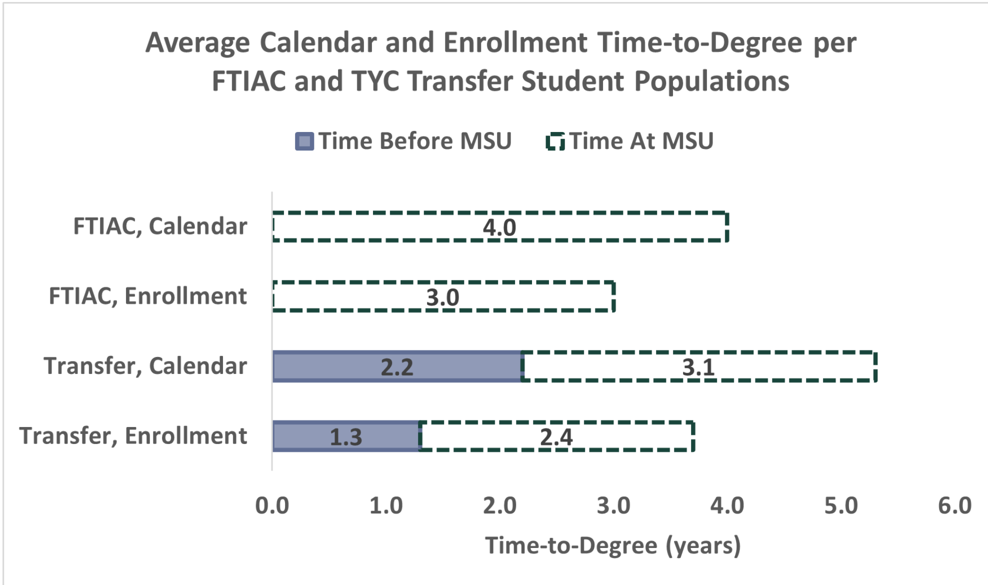


Figure 5.1 Time-to-degree for FTIACs and TYC transfer students as represented by calendar and enrollment averages, broken down by time prior to and time at MSU. For each time-to-degree calculation change from calendar to enrollment, total time-to-degree decreases, which total time in higher education for transfer students decreases by 1.6 years.

is 0.9 years ($t = 471.7$, $p < 0.001$).

To assess the average of the differences between the times, we use the t-test result, which again measures for the Null Hypothesis of difference in means of related sample scores, and the p-value reported from this t-test, shown in Table 5.4. For transfer students, each metric of time-to-degree is represented by average calculated times as designated by Equations (1) and (4). Overall, these students experience 5.3 calendar years in higher education on average, 3.7 enrollment years, with an average difference per student of 1.6 years between the metrics. The t-statistic reports significant difference with $p < 0.001$.

Disaggregated by academic level of entry, the subtraction between these averages showcases the basic difference in metrics, wherein Table 5.4 shows for transfer students a difference in total time-to-degree of 1.1 years for Freshman-level transfers, 1.5 years for Sophomore-level transfers, and 2.0 years for Junior-level transfers. Showing these individual differences per what academic level they entered as shows nuance in increasing differences of the metrics.

This difference in the TTD calculations is an increasing value as the level of academic entry, or credit status, increases. It's a simple way of showcasing the progression of disparity between

Acad. Level of Entry	Calendar	Enrollment	Difference	t-test	p-value
Freshman	4.5	3.4	1.1	64.5	$p < 0.001$
Sophomore	5.2	3.7	1.5	82.8	$p < 0.001$
Junior	6.1	4.1	2.0	62.6	$p < 0.001$
Total	5.3	3.7	1.6	97.7	$p < 0.001$

Table 5.4 The calendar and enrollment time-to-degree values, average difference in values, and t-statistic reporting significant difference for each Academic Level of transfer student.

the enrollment and calendar calculations as we parse out different levels of transfer; with Junior-level transfers having a difference closer to 2 years' worth of graduation time versus Freshman-level transfers having closer to 1 year's worth difference shown in Table 5.4. Each Academic Level of transfer student respectively bears significant difference to $p < 0.001$ in their average differences between metric calculations. Freshman transfers have total calendar times closer to a four-year graduation expectation, while Junior transfers near 6 calendar years in higher education. Calculated by enrollment, all groups of transfers meet or go under a sum of four years enrolled in higher education.

5.7.2.2 Number of Institutions

An assessment on this continues through the lens of the number of institutions attended prior to MSU, which is separated by 'one institution' and 'two or more institutions' for the sake of robustness. Once again, the latter category only contains students who attended two or three prior institutions. This is represented by the differences between the metrics, using independent t-tests performed between the population that attended 1 prior institution and the population that attended 2 or more. The differences in each group's respective metrics and the independent t-statistics between these two differences are represented in Table 5.5.

Each respective population has more than a year difference between their calendar and enrollment time-to-degree, as per Equation (8). There are very few Freshman transfers who attend more than one prior institution (N = 202). Measuring the difference of the differences per Academic Level, Junior-level transfer students have a significant difference to a value of $p < 0.001$, while Freshmen and Sophomore transfer students have p-values to less significance at $p < 0.05$ and

	1 Inst.	2+ Inst.		
Acad. Level of Entry	Difference	Difference	t-test	p-value
Freshman	1.1 (N = 1,667)	1.3 (N = 202)	-2.2	$p < 0.05$
Sophomore	1.5 (N = 2,234)	1.6 (N = 986)	-2.8	$p < 0.01$
Junior	1.8 (N = 1,478)	2.3 (N = 674)	-7.3	$p < 0.001$
Total	1.5 (N = 5,379)	1.8 (N = 1,862)	-11.2	$p < 0.001$

Table 5.5 The average difference in metrics for each population of prior institution attendance, and independent t-statistic reporting significant difference within each Academic Level of transfer student.

$p < 0.01$ respectively, showing that attending different amounts of institutions may have an effect on how much one's time-to-degree metric choice matters. Especially in Juniors, which we see the difference in metrics increase by 0.5 years, or half a year, between their calendar and enrollment time-to-degree as they attend more institutions. Though we see less increase in the difference of calendar and enrollment TTD in Freshman and Sophomore transfer students, this encourages interesting dialogue about what Junior-level transfer students may be experiencing.

5.7.2.3 Time at MSU

As we start to view these times and potential variances between them, we note some artifacts of these times: FTIAC students will only have their time at MSU considered and this time is the typical direct comparison to the total time in higher education for transfer students which includes time prior to MSU. This is in an effort to form the dialogue that if we represent the time-to-degree for non-transfers as the start and end at an institution, expanding that viewpoint to transfer students challenges the notion that the time at a single institution (their terminating institution being MSU here) is wholly representative of the time it took to graduate.

5.7.2.4 Analysis of Variance

In this section, we move away from these average differences and intend to explore the variance within and between our variables of interest. Namely, we test for differences in FTIACs and Transfers, and then the individual transfer student differences among academic level.

The mixed ANOVA in Table 5.6, performed within time-to-degree type (calendar and enroll-

Source	SS	DoF	MS	F	p-value	$\eta^2, partial$
Student Type	14,184.8	3	4,728.3	5,981.8	$p < 0.001$	0.30
TTD Type	22,804.3	1	22,804.3	136,535.9	$p < 0.001$	0.77
Interaction	1,431.1	3	477.0	2,856.1	$p < 0.001$	0.17

Table 5.6 The ANOVA result comparing Student type as depicted by FTIACs and Transfers by Academic Level, showing partial effect sizes within the sources.

ment) and between student types (FTIAC & Freshman, Sophomore, and Junior transfers) shows statistical significance of $p < 0.001$ in all of the group distinctions. There is also a significant difference between the Student Type and TTD Type. We see large effect sizes in the individual Student Type and TTD Type sources, with the Interaction having a lower, but still large partial eta-squared effect size. This tells us that among the groups, the time-to-degree metric broadly interacting with the type of student is of large effect. Expanding with a pairwise test among each specific group and interaction results in Table 5.7.

There are several interactions to unpack. Interpreting this table, we first view broad comparisons between the student types, then the comparisons between these student groups while measuring only one type of TTD at a time. While the time-to-degree is indiscriminate, we see large eta-squared effect sizes between: the Freshman & Junior, Freshman & FTIAC, Sophomore & FTIAC, and Junior & FTIAC groups to significance. Within both the Calendar TTD Type and Enrollment TTD Type, we see large eta-squared effect sizes in the **same** groups. Small effect sizes are present between the Freshman & Sophomore groups in all cases, and the Sophomore & Junior group in the Enrollment TTD case. The Sophomore & Junior comparison are of medium effect size in non-Enrollment TTD cases. These results give a strong indicator that transfer time-to-degree across the board is largely variant from FTIAC time-to-degree in either metric type, with Juniors mostly varying from every other population in either medium or large effect size. Therefore, Junior-level transfer students are experiencing much different total time-to-degree from their peers while enrollment TTD brings them at or around 4.0 years, they are still significantly different in TTD from their peers. Enrollment TTD also tends to show slightly smaller eta-squared effect sizes in each of the comparisons between

Table 5.7 The pairwise tests result comparing each Student type as depicted by FTIACs and Transfers by Academic Level, showing effect sizes within each respective interaction.

Contrast	TTD Type	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	η^2
TTD Type	-	Calendar	Enrollment	4.2	1.0	3.2	0.6	336.1	N/A	0.29
Student Type	-	Freshman	Sophomore	4.0	0.8	4.4	1.0	-18.7	$p < 0.001$	0.06
Student Type	-	Freshman	Junior	4.0	0.8	5.1	1.4	-31.5	$p < 0.001$	0.19
Student Type	-	Freshman	FTIAC	4.0	0.8	3.5	0.5	24.5	$p < 0.001$	0.17
Student Type	-	Sophomore	Junior	4.4	1.0	5.1	1.4	-17.6	$p < 0.001$	0.06
Student Type	-	Sophomore	FTIAC	4.4	1.0	3.5	0.5	50.2	$p < 0.001$	0.42
Student Type	-	Junior	FTIAC	5.1	1.4	3.5	0.5	51.6	$p < 0.001$	0.65
TTD Type * Student Type	Calendar	Freshman	Sophomore	4.5	1.1	5.2	1.5	-18.3	$p < 0.001$	0.06
TTD Type * Student Type	Calendar	Freshman	Junior	4.5	1.1	6.1	2.0	-30.2	$p < 0.001$	0.17
TTD Type * Student Type	Calendar	Freshman	FTIAC	4.5	1.1	4.0	0.6	21.7	$p < 0.001$	0.17
TTD Type * Student Type	Calendar	Sophomore	Junior	5.2	1.5	6.1	2.0	-17.0	$p < 0.001$	0.06
TTD Type * Student Type	Calendar	Sophomore	FTIAC	5.2	1.5	4.0	0.6	46.1	$p < 0.001$	0.43
TTD Type * Student Type	Calendar	Junior	FTIAC	6.1	2.0	4.0	0.6	47.1	$p < 0.001$	0.66
TTD Type * Student Type	Enrollment	Freshman	Sophomore	3.4	0.6	3.7	0.7	-16.3	$p < 0.001$	0.05
TTD Type * Student Type	Enrollment	Freshman	Junior	3.4	0.6	4.1	0.9	-28.7	$p < 0.001$	0.16
TTD Type * Student Type	Enrollment	Freshman	FTIAC	3.4	0.6	3.0	0.4	25.1	$p < 0.001$	0.13
TTD Type * Student Type	Enrollment	Sophomore	Junior	3.7	0.7	4.1	0.9	-16.1	$p < 0.001$	0.05
TTD Type * Student Type	Enrollment	Sophomore	FTIAC	3.7	0.7	3.0	0.4	50.5	$p < 0.001$	0.33
TTD Type * Student Type	Enrollment	Junior	FTIAC	4.1	0.9	3.0	0.4	52.7	$p < 0.001$	0.54

Source	SS	DoF	MSE	F	p-value	$\eta^2, partial$
Student Type	2862.1	3	954.0	2,856.1	$p < 0.001$	0.17

Table 5.8 The one-way ANOVA result comparing Student type as depicted by FTIACs and Transfers by Academic Level, showing the partial effect size.

student groups, which additionally supports a more rounded metric for student groups to see more comparable measures to each other.

In the case of comparing the calculated *differences* in time-to-degree based on Equation (8), we ran an additional one-way ANOVA through the FTIAC and broken-down transfer population to view the 'differences between the differences'. The one-way ANOVA is in Table 5.8

We see a partial eta-squared effect size that is large. This one-way ANOVA is further extrapolated on in the pairwise test in Table 5.9.

In the case of viewing the differences in each population's metrics, we see that there is large effect size between Sophomore & FTIAC and Junior & FTIAC groups, showing that taking the average difference between the metrics shows much variance in both the Junior and Sophomore populations to the TTD metric difference in the FTIAC population. There is medium effect size between the Freshman & Junior and Freshman & FTIAC groups, and small effect sizes remaining for the Freshman & Sophomore and Sophomore & Junior groups comparison. Where Table 5.7 shows that each specific time-to-degree average is significantly higher and varied from Juniors & the remainder transfer & FTIAC populations, here we see the difference in metrics concurs broadly that the transfer population tends to have larger differences in their TTD metrics than FTIACs, and Junior-level transfer students also tend to have larger differences in their TTD metrics than their peers.

5.7.3 RQ3: Facets Predictive of TTD Metrics

Exploratory analysis has already brought up interesting inquiry around what we can see of transfer experiences in our data, including potential variables we may be able to measure on our time-to-degree outcomes. Narrowing down our potential input variables, we want to begin

Table 5.9 The pairwise tests result comparing each Student type as depicted by FTIACs and Transfers by Academic Level, showing effect sizes within each respective interaction.

Contrast	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	eta-square
Student Type	Freshman	Sophomore	1.1	0.8	1.5	1.0	-13.9	$p < 0.001$	0.03
-	Freshman	Junior	1.1	0.8	2.0	1.5	-23.1	$p < 0.001$	0.11
-	Freshman	FTIAC	1.1	0.8	0.9	0.4	10.9	$p < 0.001$	0.06
-	Sophomore	Junior	1.5	1.0	2.0	1.5	-13.4	$p < 0.001$	0.04
-	Sophomore	FTIAC	1.5	1.0	0.9	0.4	30.0	$p < 0.001$	0.26
-	Junior	FTIAC	2.0	1.5	0.9	0.4	32.6	$p < 0.001$	0.51

preparing the data for prediction. In any modeling, we want to potentially see correlation between the individual input variables and the outcome variables. To further define, our input variables of interest are the following:

- Associate's Degree status
- Total Transferable Credit
- Adjusted Credit on Entry
- Top Feeder indicator
- Number of Institutions attended prior

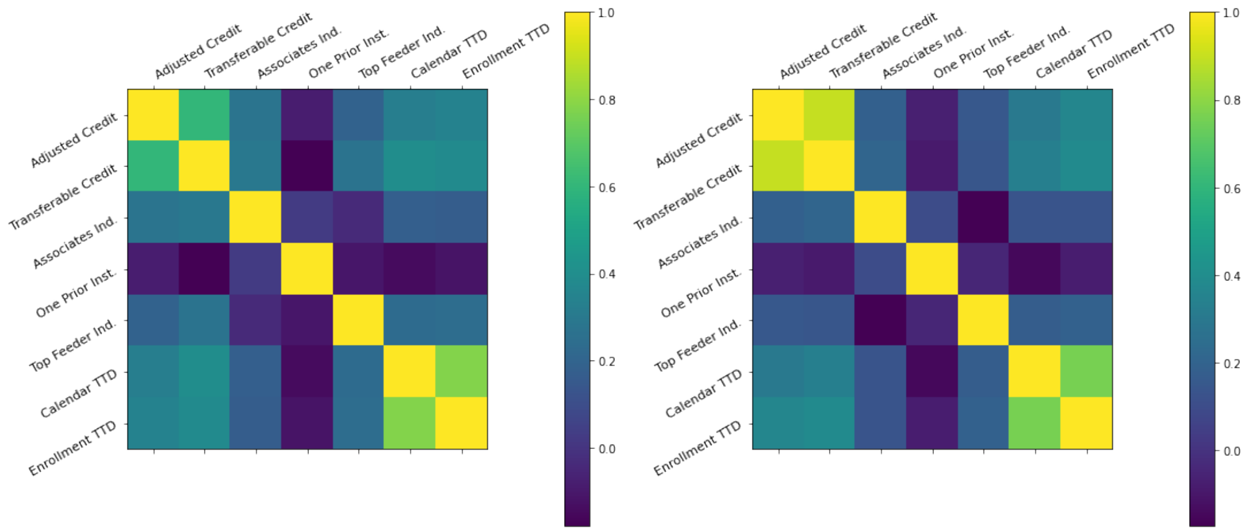
Alongside our two considered output variables:

- Enrollment Time-to-Degree
- Calendar Time-to-Degree

5.7.3.1 Correlation and K-Fold Analysis

For data preparation, we normalize our continuous data for running through the model, as well as perform a correlation matrix to anticipate which variables might have high or low correlation with each other. This practice is meant to assuage assumptions within Regression models, that highly correlated input variables may sort of 'double count' a predictiveness on the outcome, which would be unnecessary. Our current correlation matrices for all transfers, then Junior-level transfers, are shown in Figure 5.2a, 5.2b.

Among 7 variables (with both types of TTD at the ends, bottom right), the highest correlations in all transfer students are between transferable and adjusted credit (0.604), transferable credit and total calendar TTD (0.400), and transferable credit and total enrollment TTD (0.386). Slightly below these are adjusted credit and each TTD (0.327 calendar, 0.342 enrollment), the indication of Associate's degree earning and both types of credit (0.274 for adjusted, 0.293 for transferable),



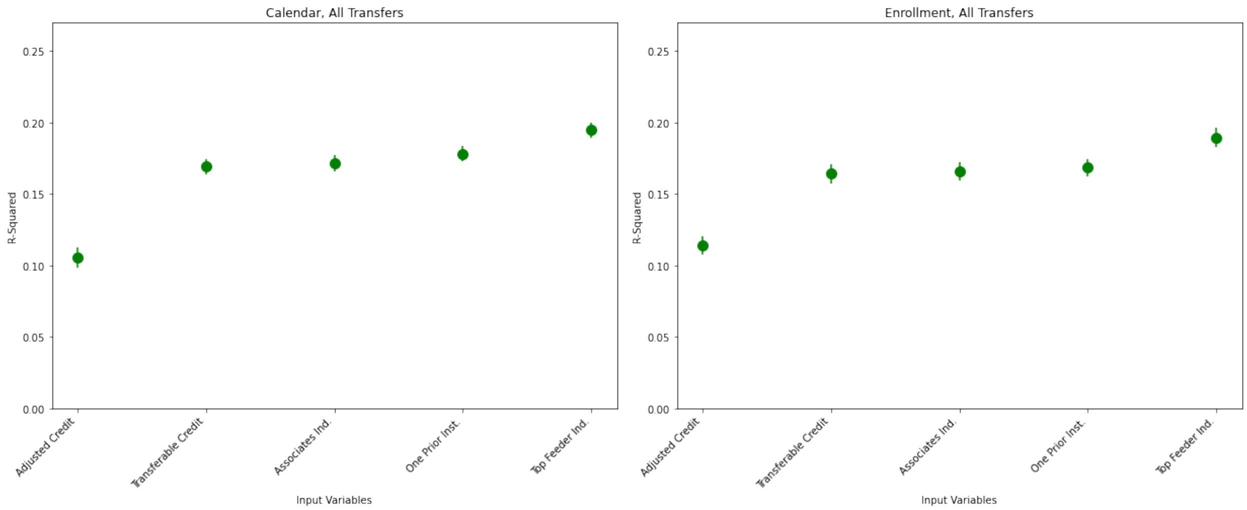
(a) Correlation Matrix for All Transfers (b) Correlation Matrix for Junior Transfers

Figure 5.2 Correlation matrices representing the correlation between our selected input variables and outcome variables, dark blue being highly uncorrelated and yellow being highly correlated.

and the call for attending the top feeder institution with transferable credits and both types of TTD (0.271, 0.232, and 0.245 respectively).

For Junior transfers only, we assess the same spread: the highest correlations are between accrued and adjusted credit (0.898), transferable credit and total enrollment TTD (0.389), and transferable credit and total calendar TTD (0.333). Slightly below these are adjusted credit and each TTD (0.304 calendar, 0.367 enrollment), very slightly with the top feeder institution indicator and enrollment TTD (0.191), and transferable credit and the indicator for earning an Associate's degree (0.208). The indicator for attending one prior institution was the only input variable to have a negative correlation with the time-to-degree outcomes.

The accrued and adjusted credit's correlation increase is important to the dialogue of this dissertation. Where accrued credit has increased to account for Junior status (holding between 54 – 87 credits), this is also where this specific subgroup are representing the majority of credit adjustment among their fellow transfer students. As seen in Table 5.2, 65.2% of Junior transfers experience some amount of adjusted credit, or 'credit loss'. These students are the most likely to interact with the policy around transferring in up to 60 credits, and so it becomes easy to see why going beyond 60 would thereby increase adjusted credit amount; the predictive power of our



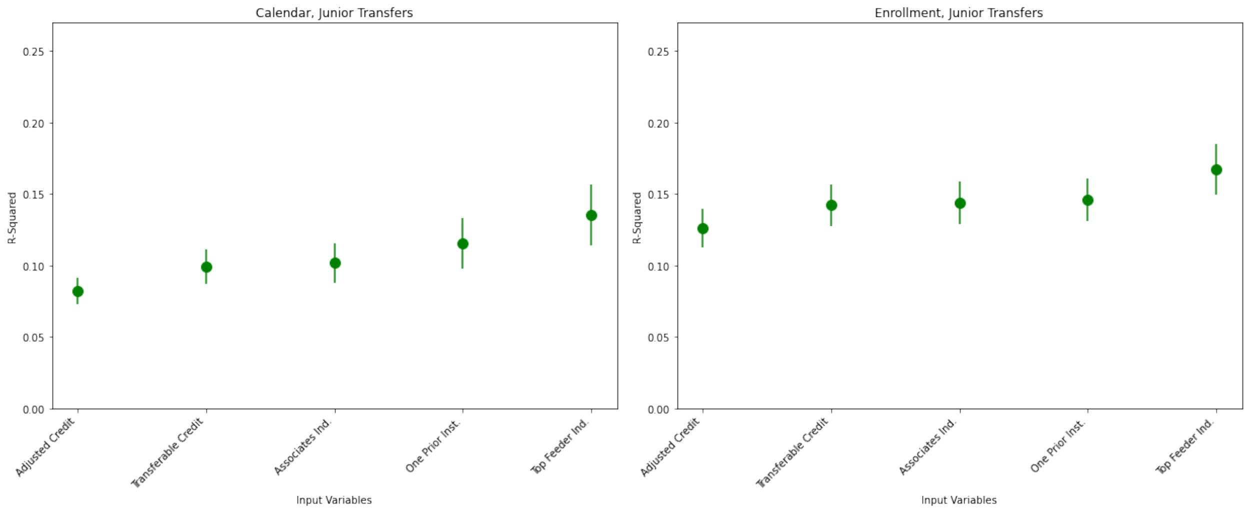
(a) Calendar Time-to-Degree Outcome, *R*-Squared for All Transfers

(b) Enrollment Time-to-Degree Outcome, *R*-Squared for All Transfers

Figure 5.3 Average *R*-Squared values from K-Fold Regression in all Transfers, representing time-to-degree as the outcome and various transfer-related input variables added sequentially into the model.

model becomes less reliable when trying to predict these variables on time-to-degree outcomes, but understanding the harm of the presence of the variable itself adds nuance to why we focus on Juniors through the remainder of the dissertation.

Considering our correlation matrix, we perform our first K-Fold run of 10 runs on calendar and enrollment time-to-degree, sequentially adding our variables in Figure 5.3a, 5.3b. What we assess from these 5 variables is that we can view the potential overlap in errors from our average *R*-Squared outputs. Again, the adding of one new variable per run means that the *R*-Squared is a collective fitness score of the singular (first run) variable, or sequentially added, every variable together as added in the model. So far, in calendar time, we see that the adding of transferable credit is outside the errorbars with an increase from *R*-Squared of 0.105 to 0.169, implying that transferable credit matters to the model as a powerful influence on the outcome of time-to-degree. The next shifts are not outside the errorbars different from each other, but our final *R*-Squared after adding all variables is 0.195. In enrollment time, we see again no overlap in errorbars between adjusted and transferable credit, moving 0.114 to 0.164. This time, the next major shift occurs in the Top Feeder indicator as the last variable added, moving from 0.168 to a final value of 0.190.



(a) Calendar Time-to-Degree Outcome, *R*-Squared for Junior Transfers

(b) Enrollment Time-to-Degree Outcome, *R*-Squared for Junior Transfers

Figure 5.4 Average *R*-Squared values from K-Fold Regression in Junior Transfers, representing time-to-degree as the outcome and various transfer-related input variables added sequentially into the model.

We can view these for our Junior transfer population as well, as seen in Figure 5.4a, 5.4b. Here, we see larger standard errorbars for these *R*-Squared averages. We see that the *R*-Squared shifts do not exceed the other *R*-Squared sequence's standard error ranges, but we see that between the calendar and enrollment plots, the adjusted credit *R*-Squared value has changed from 0.082 in calendar to 0.126 in enrollment. The end-level *R*-Squared values after running all five variables is 0.135 for the calendar model, and 0.167 in the enrollment model. This tells us that each time-to-degree outcome is not strongly predicted by these independent variables in a model with all transfers or Junior transfers, but there are strong cases after additions of credit-based variables and perhaps more exploration with the Top-Feeder indicator.

So far, we're seeing slight shifts in *R*-Squared, and not great overall value in *R*-Squareds in our models for Juniors only. We had hoped to at least compare the average *R*-Squareds and perhaps argue that certain variable additions would wildly vary between models, or that one would display a very different *R*-Squared range than the other outcome. With this not being the case, we can still perhaps argue that without any significant prediction or difference from transfer experience variables, we see that the models do bear numeric or visual differences between their *R*-Squared outputs. For Juniors, the enrollment-based model has a larger overall R-Squared value after all transfer-related variables are put through.

We also averaged the β-coefficient average for each input variable in the final model run of each TTD outcome. In Table 5.10, we showcase the input variables as columns and each final model's population with the respective time in rows. This also includes average standard error of these averaged β-coefficients. Here, we see that for all transfer students, the Adjusted Credit variable has a higher coefficient than for Junior-level transfer students. Transferable Credit, the indicator for attending One Prior Institution, and the Associate's Degree Indicator each have higher magnitudes of coefficients within the Junior population, most noticeable in the first and least noticeable in the last. We see a negative beta coefficient in the One Prior Institution indicator as well, which corresponds with the negative correlation between this indicator and the time-to-degree outcomes from Figures 5.2a and 5.2b. The Associate's degree indicator coefficient slightly decreases in the enrollment TTD outcome in both transfer populations. It also slightly increases for the enrollment TTD outcome from the Top Feeder institution indicator, but decreases in enrollment TTD for Junior-level transfer students. The Junior population also has higher overall coefficients each for the Top Feeder Indicator results.

Similar to the R-Squared results, the Junior-level transfer population has slightly higher β-coefficients in its transfer-related input variables. As well, considering the model representations with all TYC transfers still include Junior-level students, when we see that the Adjusted Credit indicator may be higher in both R-Squared averages and β-coefficient averages in the K-Fold Regression, we are considering dually that Juniors overrepresent the population who experience adjusted credit and that the model with *only* Juniors has less variation in adjusted credit than the whole population.

5.8 Discussion

This chapter is one that contains heavy meta-discussion around why we choose *how* to calculate time-to-degree, and how extending the typical calculation to transfer students advertises a time-to-degree that is beyond stigmatic expectation of students at a singular institution. Junior-level transfer

Table 5.10 The β-coefficients belonging to each input variable of the final regression model, averaged from each K-Fold run and including the Standard Error from these averaged values.

Model Population (Avg. β)	Adjusted Credit	Transferable Credit	Associate's Ind.	One Prior Inst.	Top Feeder Ind.
Calendar TTD, All Transfers	0.119	0.254	0.345	-0.180	0.283
Enrollment TTD, All Transfers	0.156	0.221	0.264	-0.114	0.318
Calendar TTD, Junior Transfers	0.014	0.600	0.383	-0.341	0.361
Enrollment TTD, Junior Transfers	0.053	0.590	0.288	-0.123	0.349
Model Population (Avg. Error)					
Calendar TTD, All Transfers	0.002	0.002	0.007	0.002	0.002
Enrollment TTD, All Transfers	0.002	0.001	0.005	0.002	0.002
Calendar TTD, Junior Transfers	0.004	0.012	0.011	0.006	0.006
Enrollment TTD, Junior Transfers	0.005	0.014	0.007	0.003	0.005

students, as well, are of high interest with regard to credit accumulation and time-to-degree. With estimated time spent in higher education being *commonly advertised* as four years, we see FTIAC students sitting around this time estimation with a difference of almost one year after changing the calculation metric from a calendar year assessment to a term-based sum. With resounding difference between the two times across all categories of the students in this dataset, we look less at the simple difference between the metrics themselves, and more at the interactions of the differences.

Hence it is unsurprising to see significance in the times within each Academic Level group. t-tests showed significance across the board, with exception to the interesting dual-level 'differences of the differences' found in Table 5.5. The two TTD metrics overall are over a year different, and two years for Junior-level transfer students. The first attempt at looking deeper, we see that comparing between the distinctions of 1 prior institution or 2-or-more allows us to explicitly calculate between the known differences in metrics of each group. These tests remained significant aside from distinguishing between the number of institutions attended prior to MSU within Freshman- and Sophomore-level transfer students. There is a half a year shift between Juniors attending 1 prior institution and Juniors attending 2 or more, in that the time-to-degree calculation shows great distinction and emphasizes shaving off 2.3 years for the latter group. Those are 2.3 years that the students were not enrolled at all and can be jarring to see those accounted for in a projected calendar year time. There was overall a significant effect from changing the time-to-degree metric and representing that difference in many comparisons, especially between Junior-level transfer students and their respective FTIAC and other transfer student peers.

Expanding upon the exploration and highlighting of Junior-level transfer students, they are by far the top earners of Associate's degrees, the ones most interacting with adjusted credit, have a higher proportion of students coming from the top feeder institution, and are more likely to attend more than one prior institution. Naturally, they accrue more transferable credit as to be called Juniors on transfer, but seeing such vast differences in their time-to-degree metric calculations calls for further exploration on why the difference is higher than the other groups of students. It is simply remarkable to see the differences in the time-to-degree metric calculations increase as we move up in credit transferability, which implies that the calendar year time is a less accurate advertisement of how long it takes to spend in higher education getting one's Bachelor's degree. Beyond the descriptive representation of this subtraction between the metrics, the one-way ANOVA pairwise tests result in Table 5.9 hits this note particularly hard: as transfer students accrue more credit, the differences between those transfer students and FTIAC students' time-to-degree metrics are much stronger. With Junior-level transfer students having 2 years of difference between their metrics, and FTIACs only 0.9 years, Juniors have *much* greater representation of graduation time through the enrollment time-to-degree metric. Representing time-to-degree in higher education becomes more realistic and looks more navigable in the enrollment time-to-degree lens.

This bolsters the intention to compare between groups of students, rounding out the story of FTIACs and transfer students, while addressing also the differences in Academic Level of Entry. As we parse through each level of the ANOVA, we can view group comparisons to ensure there are statistical differences in FTIACs and transfers of all types, but with the mixed ANOVA we are also measuring *within* the time-to-degree variables. Typical *within* measurements in ANOVA are the same type of measurement after a period of time, such as measuring a person's health before and after a medical treatment. While we are comparing the same unit of time, our measurements intend to compare whether calculating time-to-degree the two different ways shows effect in our groups of students. The ANOVA gives us the power of looking in individual time-to-degree metrics and comparing between all types of students. Seeing that the time-to-degree metric does have significant variance comparing the time metrics in all groups is mildly unsurprising, but it's within the individual times that we see our points of interest emphasized in Table 5.7.

Enrollment time-to-degree is meant to be a calculation that reflects accuracy of time and finances dedicated to higher education, and we notice large effect sizes across the board between the higher credit-accruing transfer students (Sophomore- and Junior-level) and FTIAC students. As we recall, total TTD is also different in that for transfer students, we calculate it including the time prior to MSU *and* time at MSU, while FTIACs only have time spent at MSU. Given that enrollment time is meant to portray a more 'realistic' time spent in higher education, we still are able to represent a sensible calculation of TTD while not discrediting the effort of attending multiple institutions, and we can recognize that including the prior time does shift TTD in higher education toward a 4-year mark. The enrollment time is higher for Junior-level transfer students than FTIACs and it is worth exploring more about what credit accrual prior to transfer, or adjusted credit on transfer, may have to do with TTD in general.

This brings us to the exploratory analysis utilizing Regression methods. While it may be rather impractical given our setup and available input variables, we are still able to explore the potential facets of transfer experiences that are predictive of the TTD metrics. The power of Regression techniques is the ability to look beyond statistical differences. In our study, we have two outcome variables to try and predict upon, which is difficult to compare between. It is difficult to presume one TTD calculation is 'better' for students through trying to predict on TTD with transfer-related input variables. With more students in the model for all transfers, we see much smaller errorbars within each R-Squared variable as inputs are sequentially added to the model. Viewing that transferable credits and adjusted credits are important to each TTD output is not surprising, given our views from prior sections letting us see how much different higher-credit accruing students' TTDs are from their peers. It is additionally interesting to see that for the overall transfer student population, the Top Feeder indicator is outside of the errorbar bounds from its previous iteration, which indicates a significant increase of importance in TTD from the prior variables, but a slightly higher increase in enrollment TTD than calendar TTD. This says that the top feeder indicator may have better goodness-of-fit to enrollment time than the calendar time.

As well, our β-coefficients show interesting ranges of average coefficient values, showing the transfer-related variables in each of the four TTD and transfer population models. While we recognize that the models do not train very high coefficients for Adjusted Credit, it is noteworthy the differences in the Junior population measuring within itself versus the total transfer population model that also includes them. As we noted in our background, one such interesting policy we see impacting mainly Junior-level transfer students is the 60 credit transfer limit, for which one must attain 60 or more credits to be subjected to this policy. In general, we find the enrollment TTD outcome more interestingly indicative of predictiveness from adjusted credit and perhaps the Top Feeder indicator. However, moving from calendar to enrollment TTD in the other variables show slight decreases in the coefficient outcomes.

Thinking again on what these coefficients represent, the more predictive a variable may be, the more it may change with (or against) TTD: we argue additionally that when these coefficients are smaller, this is *good* for transfer students, as we want to see TTD be *less affected* by transfer-related variables so that it is not impacted as much (e.g. an increase in one variable following with an increase in TTD). Therefore, when we see lower coefficients from enrollment TTD generally, this is a good indicator that the choice of enrollment TTD as a metric would be potentially less impacted by transfer-related traits or experiences. This also makes adjusted credit so interesting as well, seeing that the coefficients just barely *increase* on moving from calendar to enrollment TTD for both the broad and specific populations. This gives reasonable cause to exploring adjusted credit and TTD more in tandem.

5.9 Limitations

5.9.1 Data Limitations

Many limitations of this study come from the accumulation of student data. With certain columns limited by how the student data was collected, there had to be data cutting, e.g. for time prior to MSU, some students had MSU listed as a prior institution due to certain programs (such as an Agriculture Technology program) being taken before enrollment status at MSU began, so omission of these rows occurred to preserve the integrity of attending institutions other than MSU. There were also some missing data within the requested NSC data, which were automatically omitted.

Some limitations come post-cleaning, such as the low number of Senior transfer students, which were found to be mostly from programs which allowed more than the 60 credit cap of incoming transfer credits to transfer in, but as well were small enough N after outlier paring to construe total removal. This was a similar case for the students who attended more than three institutions prior to MSU, as the N of this group became too small to consider. Though our credit hour variables for transfer students are numeric and therefore up for consideration of outlier removal, we opted not to remove outliers within these variables as they are highly contingent on the academic level categorizing of transfer students, and the 60 credit transfer limit at MSU conflates Junior-level interaction with adjusted credit in particular, which also influences the removal-by-proxy of higher credit earners in our dataset. Representing time-to-degree as our dependent variable will come with the assumption that transferable credit and adjusted credit are all equally interesting and important cases, and therefore not be subjected to specifically targeted outlier removal.

Other limitations could be attributed to how data is collected at MSU, specifically that we are only performing the calculation of enrollment vs. calendar time on the time before MSU and using a flat, pre-calculated value stored by MSU for the time spent at our institution. There is also some personal inquiry in how MSU discerns the last institution attended by a student, as the National Student Clearinghouse data marks each institution in the students' repertoire as next-attended by enrollment date at each institution, whereas MSU does not keep track in this way which institution was attended 'before' another. This only slightly muddies the inquiry as to which institution was attended immediately before MSU, but we settled on using MSU's designated 'last institution type' column to identify what MSU believes to be the students' true last institution attended, narrowed down to two-year, four-year, and 'other' distinctions. Additional to this topic, we choose to sort our final transfer population as two-year college, in-state transfers, but in sorting by the last institution as being a two-year college and summing all of their prior time spent in higher education, we do not remove students who may have attended a four-year institution prior to MSU: we keep *all* transfers whose last institution was a two-year college. Students who move from a four-year to a two-year, then back to a four-year institution are often described as 'swirling' in higher education, and again we do not deliberately remove these students from consideration. The integrity of the study is kept to transfer students earning their first Bachelor's degree at MSU. Additionally, earners of prior Associate's degrees are present within both Freshman and Sophomore populations according to MSU's tracking, but though we question why they enter as these Academic Levels despite typical

Associate's granting credit requirements exceeding these Levels, we do not explore these students for more information. For review of subpopulation proportions, see Table 5.2.

5.9.2 Analysis Limitations

Tests like *t*-tests and ANOVAs have their own limitations, such as assumptions about the data scaling, whether data is discrete or continuous, whether the data is drawn from the same or different populations, etc. For our data, as we removed outliers within the time-to-degree values, we ended up with a rather large N of students and a normal distribution for incoming credit, though lost credit was not a normal distribution to begin with.

The Regression model is as well limited by several factors. There is high correlation between the credit-based independent variables, especially for narrowing down to Junior-level transfers. Utilizing both, as correlation nears a value of 1, would in essence double-contribute a variable to the model if too highly correlated. As well, not performing a full Hierarchical Linear Model technique for showcasing all possible iterations of input variables being added to the model one-by-one adds some future work in that we only explore one iteration. This is one possible story in how our individual *R*-Squared values can build up to the final model's *R*-Squared value.

5.10 Conclusion and Broader Implications

The pathway through higher education is strongly discussed in time spent, credits accrued, and overall the dedication that comes with enrollment status, [35, 36, 76, 93, 96, 97]. Since time-to-degree as a metric is already not fully agreed upon in FTIAC students, for transfer students we expected to see a lot of varied metrics [93, 96]. The question still presents itself as which method is a more accurate representation of the transfer experience. But also as a discussion about what representation is more encouraging to the projection of experience and 'how long it takes', as in if looking at the time enrolled shows a more accurate representation of financial contribution and gap-exclusive representing of that time.

From our results, we see that the evaluation metric for enrollment time consistently represents time spent in higher education closer to a 4-year expectation, to an impactful difference and effect for those who have accrued more transfer credit. As we break students by their academic levels of entry and number of prior institutions attended, we see a wider range of experiences wherein less time is taken the fewer credits one has accumulated and the fewer amount of institutions were attended, including a smaller gap between the two calculation types. Expanding on transfer-related variables is part of a stronger conversation about what it means to graduate 'on time' and how we can calculate that with the specific time-to-degree metric. While the Regression modeling for *predicting* time-to-degree needs more exploration, exploring each input variable, we can see how each metric's model shifts, but as well which inputs may be stronger/weaker with respect to the other calculation type's model. Since the calendar year and enrollment type models are not explicitly compared, we open the discussion of time-to-degree such that calendar time-to-degree may be less predicted by transfer-related input variables for our Junior population than the enrollment time-to-degree. Junior-level transfers are worth exploring more.

From a policy perspective, students are subject to the institution's whim considering what barriers they will encounter upon entering their destination institution. However, the culmination of their higher education experience is from all institutions attended; each of those institutions' policies influence their decision-making and their trajectories. Choosing to enroll and dedicate one's self to acquire credits requires careful consideration of the credits potentially already held and the policies remaining along the way that depict barriers of what credits they still need or from there until graduation. From our data, we know that students spend a long time at institutions prior to MSU, especially Juniors and Seniors from our top feeding institution, and so for these students who transfer to MSU, they are required to spend the Junior/Senior tuition rate and will need to do so in whatever time it takes for them to attain the remaining credits needed to graduate. As such, more conversation about loss of credits and credit applicability are desired, especially for these transfer students who have dedicated their time and money significantly to higher education.

CHAPTER 6

ASSESSING CREDIT LOSS AS AN INTERACTION WITH THE 60 CREDIT TRANSFER LIMIT

6.1 Purpose of this Chapter

In a framework of challenging institutional policy within the lens of transfer student success, there is a recurring question of which policy one may be addressing or critiquing. In the pathway of two-year college (TYC) transfer students, there are many policies encountered regarding the accumulation, articulation, and translation of their credits between institutions. In this study, we analyze credit loss as broken up into numeric and identity-based loss and view its potential effects on enrollment-based time-to-degree and excess credit on graduation. This is conducted primarily on Junior level transfer students transferring from TYCs, first broadly from enrollees in a range of enrollment years 2010-2016, then to just Junior transfer students in Physics from this time frame to view more detailed accounts of the number and type of course credit lost and particularly de-identified. Results indicate that for all transfer students, excess credit on graduation and time-to-degree do not seem to be strongly impacted by GCU credit level differences, until disaggregated by academic level, for which Junior-level transfer students compared with their peers show that those with more than half of their credits being GCUs become significantly different, to a higher effect. As well, transfer students with or without adjusted credit have a significant difference in time-to-degree to large effect, especially evident in recognizing that Junior-level students represent most of those who experience numeric credit loss. Exploring Physics majors additionally unfolds the general statistics of the *types* of courses brought in and, of how many courses come in, the average that are comprised of GCU credit. In all, we find that credit loss is an important aspect of graduation-level success, more to an affect on enrollment time-to-degree than excess credit accumulation.

6.2 Introduction

While time-to-degree has been one of the standard metrics used to demonstrate student success, the experience of being a transfer student might impact this measurement and the financial implications underlying it [35, 36, 76, 93, 97, 103]. For years, institutions have utilized a measurement for time-to-degree (TTD) that represents the total time that a student spends at an institution from the time that they begin to the time that they graduate, challenged by works such as Yue and Fu [96]. Transferring institutions often comes with barriers that take time to navigate, such as the translation of any credits earned at a previous institution, and as explored in the previous chapter, the different means of choosing to calculate the time it takes to graduate in total can have implications for transfer students in particular.

TYC transfer students encounter policies designed around the maximum amount of credits allowed at the destination institution and the nuanced adjustments made in order to meet that criteria [7]. As such, credit loss occurs for students who reach beyond this maximum. The credits need to be identified and translated, counted for existing credit hours, and then applied to the degree pathway, potentially impacting a student's TTD. This process bears implications around transfer policy and financial cost of attendance, but as well the simple recognition of credit loss as a factor that impacts TTD is one that is recognized in *survey* and *interview* analyses such as Glass and Bunn or Hodara *et al.* respectively, bolstered by Cullinane's work [7, 35, 103].

In this chapter, we explore credit loss as a phenomenon of two different factors: numeric credit loss (adjusted credit on entry) and credit identity loss (incoming credit that is identified as General Credits — Undergraduate (GCU)). These aspects of 'loss' consider both *financial* and *attritional* values of credit, where adjusted credit once paid for now must be re-fulfilled at the destination institution. Credits re-identified as GCU de-identify courses that previously could have fulfilled specific degree requirements. These aspects of credit loss shape a common theme in that many transfer students are impacted financially when accumulated credits lose their influence and hinder the transfer process [75, 94]. Attewell and Monaghan target specific policies such as one in West Virginia which removes a certain program's aid to students if they do not take 30 credits of courses per year, recognizing in their own work that 15 credits per term is a remarkable proponent of timely graduation, and *recommending* that policies address and aid the population that take less than 15 credits typically [75]. While this recommendation is sound within their findings, it still proposes the question, how do we recognize when we are perpetuating the control of harmful policies? At the end of the day, there is still a program existing wherein student aid is lost if 30 credits are not taken per year, which is an increasingly financially infeasible target. Per relevance to TTD through Attewell and Monaghan's work, we wonder that with credit momentum increasing, more credits may be earned in a timely manner, but then how one takes more care into taking the *right* increase translation power.

6.3 Refined Background

Where the previous chapter of this dissertation dealt with an assessment on success metrics as a side to policy, this chapter finds fuller focus on a specific policy. Our findings prior highlighted a need to recognize when policies are *harmful* or *helpful* to transfer students. Our efforts of forming a different TTD metric were with the intent to view TTD through the lens of transferring and transfer experiences; Chapter 6 will use the metric of TTD supported by Chapter 5 of enrollment-based TTD as a backbone to viewing a specific policy and further the dialogue on its helpfulness or harmfulness.

This section brings forth literature that pertains to credit loss, general policy related to credit accrual and articulation and topics relevant to the 60 credit transfer limit. This lays out a deeper look into the landscape of transferring credit and where credit loss is explored in other research and this chapter.

6.3.1 Centering Time-to-Degree & Case Study Policy

We have recognized TTD as a success metric, among other more amply studied graduation metrics like graduation rates in transfer students [46, 59, 71, 72, 105, 106]. We have already challenged the perspective of TTD as a success metric for transfer students, but now add this new lens of credit accumulation within transfer students. A valid starting inquiry is, is credit accumulation part of a policy, or part of a success metric? As we bring in our framework of data-driven policy, this question will be fleshed out as a dialogue on the complexities of earning and losing credit.

At many four-year institutions, 60 credits is the maximum that students can apply from their prior institution(s) to their destination institution [107]. As a local example, transfer students under the Michigan Transfer Agreement must satisfy certain specific course requirements, some of which may not apply to their degree pathway other than as elective credit [108]. At Michigan State University (MSU), the last 30 credits of a degree pathway must be earned at MSU, ceasing the potential of courses being taken at other institutions (e.g. during a Summer semester). These examples begin a conversation around unique transfer experience interacting with policy, in that accumulating more than 60 credits becomes a waste of money if not allocated efficiently, and the credits earned at MSU must build efficiently from that which has already been accumulated. Projected time-to-degree for transfer students could then increase with those poorly allocated credits.

6.3.2 Connection to our Data-Driven Policy Framework

As students encounter policies, their experiences shift to fit those rules. Institutions then evaluate students' interactions with and outcomes from the policy. From this evaluation, policy makers can (and should) then produce new inquiry about those student outcomes that can influence future policy iterations or creation. We've established that higher credit earning has an effect on the difference between choices of TTD metric, and therefore the impact of changing or making the metric enrollment TTD for transfers. So then, the bolded part on evaluating students' interactions with — and outcomes from — the policy, is that TTD is already an established outcome, we just need to see it in tandem with an existing policy.

This brings us back into our interest in credit loss, in that it occurs most frequently in Juniors, and that we see adjusted credit sprout in tandem with the 60 credit transfer limit. For this, we will refer back to Figure 2.1 in Chapter 2. The credit transfer limit is an existing policy at MSU for transfer students from TYCs and, in this chapter, has us not establishing or forming research questions within a metric for student success but instead stepping back to view what policy may interact with that metric. In this chapter and through the framework, we encounter inquiries such as, what *is* credit loss, how do we mitigate it, and when do we intervene? But stronger to the research questions we will frame later, our main inquiry is, how does credit loss relate to TTD, if at all? These questions must first revisit our framework for better understanding of policy and how it shapes the transfer space.

As we visited in Chapter 2 as a prime example, Reverse Credit Transfer is a policy being enacted across the United States in order to aid transfer students in finishing their Associate's Degree [9]. This is a policy that has been implemented in order to aid transfer, allowing researchers to evaluate its effects within transfer student success [30–32]. In a broader scope, this example of a data-driven approach to policy implementation encourages the challenging of historically in-place policies, especially for transfer students. Other policies may have once been data-driven, but are historic enough to challenge and reform inquiry including how students are harmed or helped by them [7, 33].

This foundation of inquiry generation sparks the continuation of challenging, revising, and creating policy. While Reverse Credit Transfer is just one example of a policy that transfer students encounter, others exist as potential focuses for deeper inquiry. Here, we will focus primarily on the 'maximum number of transfer credits' policy that is present at many Bachelor's Degree Granting Institutions and how it impacts credit loss for community college transfer students.

The maximum number of credits a student can *typically* transfer in to MSU is 60 credits, which will be a value we keep track of closely in this chapter's analysis. However, it's important to understand that while this is a policy that we can actually target, the specific limit can vary from institution to institution [107] and so it presents no typical national 'standard'. This in itself is an interesting point: if there is no agreed national standard, then why choose this specific amount of credits as the typicality for those transferring in to MSU? The general consensus is *around* 60 nationally, but not consistently; there are still a series of conversations within each institution on how to depict the merit of earning a degree, what coursework style and content they offer, or other contributing factors to earning a degree from *their* institution as evidenced by the saturation of articulation agreements between institutions [7]. In my search for perspectives on credit mobility, I found an interesting historic perspective into designating which and how many credits can come from specific institutions in Louisiana [109]; today, there are several institutions now to keep track of that have all been growing the past several decades, and so their individual specializations, programs, majors, student admissions, and graduation requirements are all different enough and large enough to create complications when attempting to figure out what equates and where. Bringing it back to the framework in our current perspective expresses, then, how many different variables and factors go into credits losing power, of which we choose to focus on the transfer limit for a tighter focus.

While we address a specific policy within the 60 credit transfer limit at MSU, our framework allows us to view credit translation as an inherent and 'unspoken' policy underneath the transfer limit. That is, while specific courses may have perfect 1-to-1 translations between the prior institution and MSU, there are still droves of courses or credits which become 'General Credits — Undergraduate' (GCUs); 60 credits may still be satisfied with these credits held, and these credits are also typically prioritized in adjusted credit so that students may keep their specific course credits. However, credit translation being an institutional decision makes it the true culprit of this study, where the 60 credit limit is a numeric foundation for some of our simple comparisons. MSU's choice of 60 credits may not be budged by this study, but we can delve deeper in what that limit's underpinnings suggest for transfer students and how they can navigate MSU's post-translation of their credits.

6.3.3 Understanding Credit Loss in the Literature

Hodara *et al.* on explores credit loss in a modern perspective [7]. This is a ten-state study in which they explore several aspects of credit attrition, mobility, articulation agreements, and defining institutional policies of these ten states with regard to transferring credit. Specifically, it is named that credit loss can occur both in a literal 'these credits do not count toward graduation' sort of *numeric* perspective, and then as a 'these credits do not satisfy courses in your intended degree' sort of *identity* perspective.

Tying back to our defined factors of credit loss, we view this in Hodara *et al.*'s definition, that literal numeric loss is important, but so is the less-stated but impactful loss of de-identifying previously passed courses in the translation process between institutions. They specifically mark the identity-based loss as 'degree program credit loss', or credits that are specifically de-identified from the student's *degree program* such that the de-identified credits might have satisfied credits required to graduate with their degree [7]. It is a means of separating elective credits from degree credits. While we agree with this view, we will later use *all* de-identified credits in our analysis, as any courses that could be named and satisfied could eventually have power in the degree pathway, especially in the event that the student changes their major.

Hodara *et al.*'s study is the epitome of using research and data to address and critique existing policy, with particular regard to transfer student success and credit mobility [7]. Part of their recommendations is to 'determine policy effectiveness' through the 'improvement of data systems' and 'research on credit mobility', which follows our framework in its entirety. But further, from viewing the 10-state study and finding that credit loss both in its numeric and identity form are harsh challenges to transfer students, with recommendations for strong advising and early intervention to identify what pathway students want to take.

Even more recent studies help contextualize credit loss [110–112]. While Hodara *et al.* address wide policies across several institutions, Richardson's many works narrow in particularly within the realm of Engineering majors, showcasing multi-institutional views of losing credit, single-institutional views within Virginia Tech for deeper programmatic analysis in Engineering, and defining credit loss in various manners, including another numerically-based definition of credit loss in the form of *excess credit* [38, 110, 112].

While we have stated that there are a couple of ways credit can be lost on transfer, we have not yet discussed Richardson's perspective on 'excess credit' accumulation [110]. It is a phenomenon related to graduation, wherein the student exceeds the amount of credits needed to graduate. This is *not* a measure unique to transfer students, as any student type can experience an excess of credits on their pathways to graduation. Richardson explicitly explores excess credit on part of remarking and reinforcing prior studies' conclusions that, as transfer students experience credit loss, they also experience both excess credit accumulation and longer time-to-degree [38, 103, 113].

Within many of these studies, especially Hodara *et al.*, there is recommended early intervention for getting a pathway firmly set for students such that their transfer can be streamlined [7]. But it's worth asking, how early can early intervention possibly be to where the integrity of its intention actually comes to fruition? One can only intervene to an extent where they are simply railroading students into study that they may not be interested in any longer. Richardson pushes the narrative more toward recommending data sharing agreements between institutions and further study into credit loss's effects on time-to-degree and financial implications [110–112].

6.4 Research Questions

As we will describe our research methods below, first we pose the following Research Questions as foundation for the remainder of the paper:

1. To what extent does credit loss occur in two-year college transfer students?
2. What effect do the defined facets of credit loss (numeric & identity) have on enrollment time-to-degree and excess credit on graduation for each academic level of transfer student?
3. For Physics two-year college transfer students, to what extent do we see the defined facets of credit loss occurring and in what ways can we delve deeper into GCU allocation and transferred credit for the Physics curriculum?

6.5 Refined Methods

Thus far we have established a particular relevance of our named policy and interests toward Junior-level transfer students, and as well have established preexisting definitions of credit loss in higher education through other literature, but we have yet to define credit loss explicitly within our study as a calculable measure. After establishing the population without further deviation from Chapter 5 aside from additional context of courses transferred in and adjusted off, we choose to measure credit loss in two main calculations, and one fine-grain analytic calculation.

In our analysis below, we explore adjusted-numeric credit loss and GCU identity loss through the lens of descriptive statistics. The student population in this study includes in-state TYC transfer students who enrolled at MSU between 2010 and 2016. The disaggregation of these credit loss metrics by academic level on entry to MSU shows a deeper insight into how many credits are lost per individual. Further investigation breaks students up by those with or without credit loss and

Category of Students	N
Freshman Transfer	1,857
Sophomore Transfer	3,220
Junior Transfer	2,152
Total Transfer	7,229

Table 6.1 Final population of TYC transfer students comes to 7,229 students after removal of outliers in time-to-degree values, students who attended more than three prior institutions, and Senior level transfers in low N.

how TTD and excess credit might shift between these groups, especially considering academic level of entry. This allows us to form starting dialogue not only on the definition of credit loss, but on potential metrics of transfer student success that may be impacted by it. Lastly, we view these through a tighter lens of Physics majors to encroach inquiry around a smaller view of students, what we continue to be able to measure about these losses and success metrics, and the other nuanced data we can gather from our dataset for a specific major after enrollment.

6.5.1 Sample

This chapter uses the same population criteria as established in Chapter 5. This decision is made with the intent to continue utilizing the same dataset that curated the time-to-degree metric calculations. This is true as well for continuing the outlier removal decision through only the TTD metrics, which leaves us with the same starting population of 7,241 TYC transfer students with the omission of Senior-level transfers. This decision stems from complications around special transfer criteria in certain majors at MSU which may allow for the transferring of additional credit beyond the typical 60 credit maximum for TYC transfers. Otherwise, this data is from the same joining principle SQL pulls as Chapter 5, after which additional information is joined from new SQL pulls to showcase course information coming in and received at MSU. New SQL pulls are comprised of prior coursework and continuing to display the number of transferred credits on enrollment, both of which can be found in Appendix A. Our final starting population is 7,229 total TYC transfer students spanning enrollment at MSU between 2010 and 2016 after removal of 12 students with additional missing data. The breakdown by academic level of this population is found in Table 6.1.

With these we are able to discern the type and amount of credits accrued per student from prior institutions, as well as the type and amount that were accepted as transferable to MSU. This is an important language distinction: the translation of credits that occurs must meet a few requirements in order to be accepted for transfer, then thereby being considered ‘transferable’. The total amount of credits held by these students being called ‘transferable’ and stands at a value in conjunction with the amount that is ‘adjusted’, as established for defining adjusted credit in the prior chapter. We view transferable credit now more plainly as the amount that is accepted and applied to existing MSU coursework if specific enough, then which the remaining amount (usually as GCU) satisfy degree credits toward graduation up to 60.

Highlighting Juniors allows us to see the exact and fruitful population that interact with the 60 credit transfer limit. With an outcome such as time-to-degree, we can not only view how much credit loss is occurring or of what type, but also narrow further into the Physics curriculum in our final lens for specific programmatic views of credit loss and what courses may be anticipated to be brought in with Junior transferring Physics majors, but may be de-identified. Tightening in the lens toward discipline-specific study aids in understanding closer perspectives of credit loss per a narrower frame of course requirements, inspired by the Engineering credit loss literature explored previously [110, 112]. This discipline-specific focus is expanded further in Chapter 7 where we permanently focus on Physics majors.

Physics TYC transfer students are also assessed for another lens of credits, i.e. credits on graduation, in which we have retained information on what major they began as, the major they graduated, and can view how many credits total they graduated with. Therefore, it may be of interest to pair these graduation level credits with how long it took these Physics folks to graduate, set alongside the information about who may or may not have graduated with Physics degrees, but who began as Physics majors. For our population of TYC transfer students from 2010-2016, we consider the population of Physics students in Table 6.2 below.

For the purposes of more robust information, we elected to choose the population that enters as Physics majors within our cohort range. The decision to enter into Physics as a transfer student can

Category	N Students
Entering Physics	85
Graduating Physics	24
Entering AND Graduating Physics	13

Table 6.2 Number of Physics students considerable in this chapter, where Entering Physicists and Graduating Physicists overlap by 13 students, otherwise graduating 24 TYC transfer students in Physics between 2010-2016

be interesting at MSU as a case study because of a local tendency for Physics students to at some point be associated with (or attempt to graduate from) the College of Engineering. With our work in Chapter 7, we will be able to explore more about the pattern of coursetaking after enrollment at MSU as a Junior to be able to make inferences about deciding to graduate or not with a Physics degree. In this chapter, we will focus mostly on our more basic representations following TTD and excess credit, as well as incoming credit for a broader perspective on success.

6.5.2 Course Equivalency Process & Our Definition of Credit Loss

This analysis explores several nuances around the concept of credit loss. The institution of focus documents all previously earned credits, and as such, the policy for TYC transfer students of ‘maximum allowed transfer credits’ defines the need for an adjustment, which leads to transfer students experiencing credit loss. If a student reaches the limit of allowed credits upon entry (60 credit hours for TYC transfer students), then any additional credits would be captured as a sum of how many did not apply to their degree attainment. While this is one way of documenting the impact of this policy, the nuance extends past these adjusted credits upon looking at the transfer student’s pathway through higher education.

As we unfold defining our distinction of what credit loss is and how we calculate it, first we have to understand what MSU has the ability to measure. This will help us uncover a little bit of that black box. It was hard work for us to connect to MSUEDW in the first place, but the proceeding hassle was navigating what information they store. We know that there is a way MSU logs prior institutions attended, though it is not to term-level attendance like the NSC data is. What MSU logs additional to that is the acceptance of existing credit, existence/need of translation in the system,

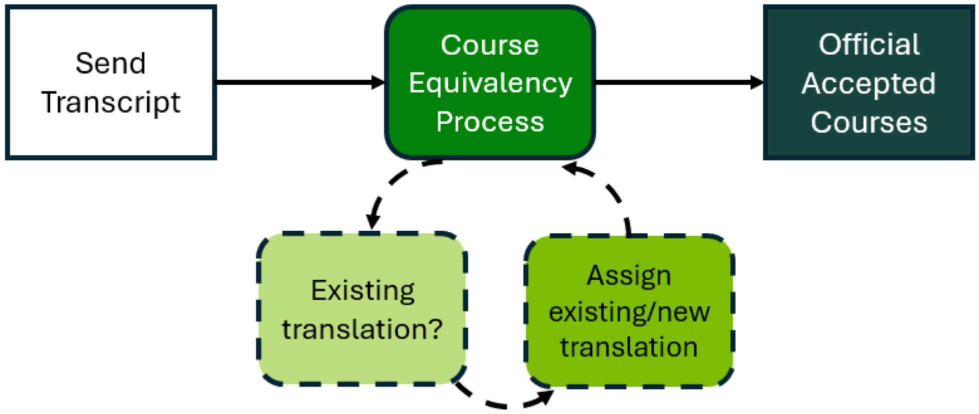


Figure 6.1 In the process of transferring and translating held credit, the student begins with a transcript, and the institution decides an equivalency for all accepted credits.

credit worth, and course code reality after translation. This process is reflected in Figure 6.1. Both the course code and subject matter to some respect, as when credits become MSU GCU credits, they are designated (not in the database) as related to the degree or unrelated.

At their prior institution, the student receives a 'credit earned' designation for each course taken. Upon transfer, the earned courses are translated to an equivalent course at MSU. These translated courses earn a new identity in course code and credit hour allocation, as well as potentially being designated as GCU, which are credits that can count for the credit needed for degree attainment, but are not applicable for specific major or minor course requirements. With this designation, the course credit from the prior institution has lost its identity and thus has the possibility of impacting a transfer students' TTD.

Much of this process is, as stated prior, quite the 'black box' of occurrences: which courses are the 'right' ones to take to translate 'perfectly' and place you exactly where you need to be upon transfer? As you transfer, the translation of courses is a process unfolding into several subtasks (Figure 6.1): each incoming course is assessed for an existing translation and, if one does not exist, several tasks occur to gather the course description, syllabus, and inquire to the potential related department what course they believe is equivalent. Which courses get 'perfectly' translated is a matter of not just preexisting course translation efforts from common institutions, but also the course contents themselves. How is it known that the courses are exactly equivalent, and what happens if a transfer student enters a course at MSU that is, essentially, a course they've taken before? Lastly, this black box expands in the adjusted credit, as courses are accepted from TYCs up to 60 credits. It is known, too, that all courses accepted and translated are counted as satisfied at MSU even beyond 60 credits, so it is not a matter of 'which courses are adjusted off?', but rather 'how do I attain 60 **additional** credits to graduate with 120?'.

To explain further, incoming credit will either satisfy specific course and subject codes at MSU or have a subject code and GCU allocation. TYC transfer students, as affected by the 60 credit transfer limit, must take at least 60 credits of courses at MSU after transfer: any of their prior held credits are subjected to assessment for proper articulation and are able to satisfy MSU courses on paper. For example, a transferring Physics major may have 70 credits to their name and perhaps all of them are articulated and accepted for transfer such that all named post-translation courses are considered completed and GCU credits are allocated per department. In this example then the student still needs 60 credits to graduate, even if they have satisfied 70 credits worth of courses. Many consider the '10 adjusted credits' to be any GCU credit, as there is no *specific* course being written as completed, and GCUs count toward graduation credit, but do not satisfy specific courses along the pathway to graduation.

Regardless, the translation results in a set of MSU courses coming in, named in MSU's credit amount and course code view. The student now must enroll in their pathway courses and figure out which courses are next in their degree at MSU. What courses are left to take, what ends up applicable, how many credits are left to fulfill; it's a confusing cocktail that is unaided in interpretability by the data we have and is often left to the student to figure out.

We have the number of transferable credits, adjusted credits, how many credits become GCU, and the course subject associated with that GCU spread. The tough part about separating credit loss in numeric and identity calls is that numeric is easy to interpret, that the number adjusted will have to be made up in order to reach the graduation requirement; the identity is harder to interpret, that students will technically have these credits on their ledger but really nowhere solid to put them. When we define it, we typically stack all GCU credits as a general amount of GCUs owned per student, represented as a proportion of their transferable credit (% of total). This is represented as a total of all transfers, or of proportions within each transfer academic level of entry.

On exploring GCU credits further we found that only 60 students in the total 7,229 transfer students *did not* hold any GCU credits; in other words, 99% of TYC transfer students in our dataset hold some amount of GCU credits. We will view a distribution of the GCU credits held in our results.

As well as defining these aspects of credit loss, we visit the identified phenomenon of 'excess credit accumulation' as a graduation-level metric. We are interested in viewing, in addition to whether TTD is impacted by credit loss, whether there is interesting effect on excess credit at graduation as well. This is calculated as a conditional subtraction that takes the amount of credits held at the graduating term and subtracts the amount of credits needed for the degree program. At MSU, this latter amount is typically 120 credits, but for most majors within the College of Engineering, there are 128 credits required to graduate. We took this into account and, as stated, conditionally subtracted 128 credits for the specific required majors. Applied Engineering majors' graduating credits are a special case as they are required to have 133 credits on graduation if they choose a Business Analytics concentration. Since this is not specified in the data, we presume to subtract 120 credits from their graduating amount, which is already atypical from the other Engineering majors.

6.6 Analysis Methods

6.6.0.1 Descriptive Statistics

Shaping credit loss with the identity- and numeric-based definitions brings us to represent through our data what we see through de-identifying and adjusting off credits. In Table 6.3 we view the identity lens by showing how many credits held by students are GCU credits, shown as a proportion of their total held credits. Again, this is a designation of the course code, such that a GCU credit can have a subject accreditation (e.g. a math GCU, a chemistry GCU, a physics GCU, etc.). The translation effort often results in GCU credits coming out of inexact course translation in terms of credit amount, (e.g. a course being worth 4 credits at the prior institution may be worth

Academic Level of Entry	Avg. Proportion GCU	N
Freshman	44.8%	1,857
Sophomore	42.4%	3,220
Junior	38.3%	2,152
Total	41.8%	7,229

Table 6.3 Average proportion of GCU credits held by TYC transfer students, showing the amount of post-translated credits that are not associated with a specific course. The total percentage of credits coming in as GCUs is 41.8%.

a 2 credit course at MSU, so 2 credits become GCU credit). With this in mind, we view the total average proportions of GCU credits held.

The reason that academic level of entry matters to this proportional value is that, according to the amount of credits needed to be in each academic level distinction, this changes the literal amount of GCUs owned. See Table 6.4 for the spread of credits in order to be labeled in each academic level of entry group. As examples, if one is a Freshman transfer who owns 12 credits coming in to MSU, if the average GCU amount applies to them, about 5 of their credits could be GCU credits. If one is a Junior transfer, though, perhaps with exactly 60 credits coming in, this average proportion would translate to about 25 of their credits. For the Freshman case, that could be one or two courses that have become de-identified. For the Junior case, that's at least six courses de-identified, assuming the maximum course credit value, 4 credits per course. In Figure 6.2, this represents the spread of all GCU credits as a proportion owned per student. The average proportion of credits owned by transfers that are called GCUs is 41.8% of their credits.

Additionally, in exploring a bit more on whether there is merit in creating a binary indicator for whether a student has zero or non-zero held GCU credits, like having or not having adjusted credit: we found that only 60 transfer students did not have any GCU credits held. Thus, we shift our perspective. We consider instead the proportion of credits per student and look above or below a threshold of 50%, as per whether half of their credits became GCU credit or not. This decision was made with consideration of what threshold breaks past a 'typical' or 'reasonable' amount of de-identification. With how prevalent holding GCU credits is, we initially considered measuring

Student Level	Credits Required
Freshman	0-27
Sophomore	28-55
Junior	56-87
Senior	88 or more

Table 6.4 The range of credits per grade level distinguishes the whole student body by how many credits they hold.

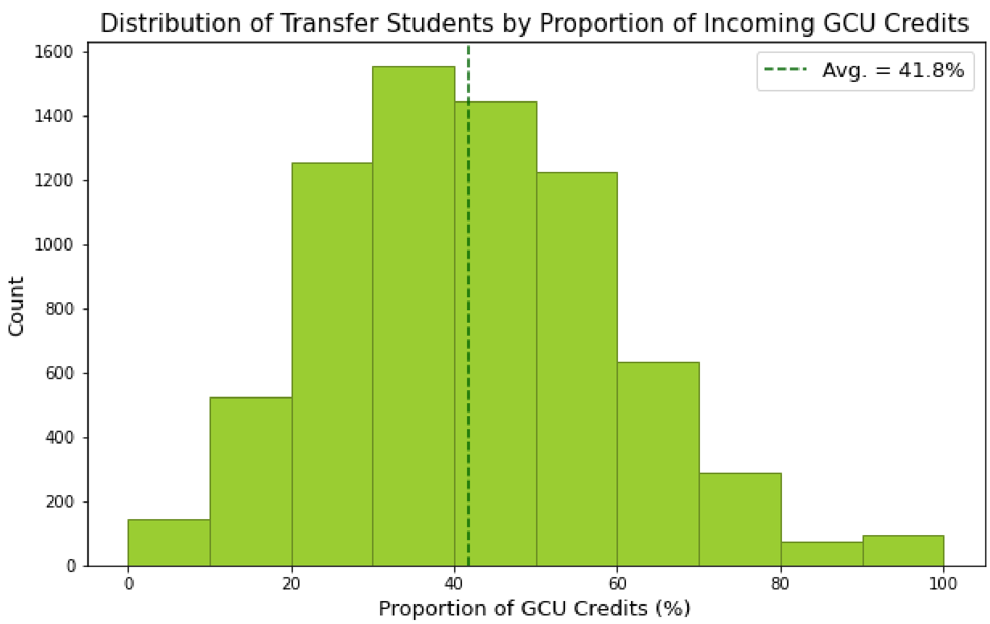


Figure 6.2 Histogram distribution of General Credits — Undergraduate, as a spread of the proportion of GCU held per student. The average proportion of GCU credits held is 41.8%.

above or below the mean proportion of GCU credits held by the total population. Settling on above or below 50% proportion pushes more into an equivalent idea of 'half of my incoming credits don't have a specific course associated with them', a rather jarring perspective.

6.6.0.2 Effect Size & Graduation Metrics

The relationship between our credit loss distinctions and our graduation metrics is performed through an effect size calculation. Effect size is a measurement that dictates on a scale of small-to-large the proportion of variance associated with each effect or interaction of effects [91]. In a broad example of effect size, there are perhaps two groups to compare means between: we find out that the group 1 and group 2 means are significantly different through a *t*-test and a significant *p*-value result. However, while we identify they are significantly different, we have little context to *how* different the means are. An effect size contextualizes this through that small-to-large range, wherein a small effect size is not a very strong difference, while a large effect size is a very large difference.

Our choice in effect size is Cohen's *d*, which is performed in Python with a defined function and various 'numpy' library calculations [85]. Cohen's d has a deceptively simple equation:

$$d = \frac{\overline{x}_1 - \overline{x}_2}{\sigma}$$

This equation takes the mean of population 1, $\overline{x}_1$, and subtracts the mean population 2, $\overline{x}_2$, then dividing the whole subtraction by standard deviation σ. However, this standard deviation is actually a 'pooled' standard deviation. This is calculated with the intent of comparing *two independent samples*, which follows cleanly with an independent t-test to contextualize the effect size calculation. The pooled standard deviation is calculated by considering the sample size of each population (n_1, n_2) and their respective variances (s_1, s_2), the latter of which measures how spread out the data is from the mean (generally displayed below by a population p's variance s_p).

$$\sigma = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}},$$
$$s_p = \frac{1}{n_p - 1}\sum_{i=1}^{n_p}(x_{p,i} - \overline{x}_p)^2$$

Cohen's *d* is represented with the ranges supplied in Table 6.5. When an effect size between two independent populations is calculated, the effect size must meet the minimum value per range (e.g. a small effect size is named when the calculation reaches at least 0.2); anything less than 0.2 is considered negligible difference.

As well, we supplement our results with more pairwise *t*-tests to help compare specific groups of transfer students that are affected 'more' or 'less' by our defined credit loss on graduation metrics. We explored Analysis of Variance heavily in Chapter 5, but here only consider the comparisons

Effect Size	Value
Small	0.2
Medium	0.5
Large	0.8

Table 6.5 Effect size range per Cohen's *d* result minimum comparison, where the value must be met in order to be considered within the Effect Size range.

supplementary to discuss how each credit loss may have individual variance from other transfer students. Therefore, we bring back the defined ranges of the Eta-Squared (η^2) effect size. Please see Chapter 5, section Analysis Methods, Analysis of Variance for an explanation on ANOVA techniques, pairwise *t*-testing, and Eta-Squared effect size reporting. This results in Table 5.3, which we use again as the range to define small, medium, or large effect size for Eta-Squared effect sizes.

6.7 Results

6.7.1 RQ1: Credit Loss for TYC Transfer Students

In descriptive statistics, it's important to distinguish each of the levels representing percentage groups. As we view each level of transfer student, we note in tandem that Juniors collect more credit, adjust off more credit, and simultaneously have a slightly smaller proportion of their incoming credit that becomes allocated as GCU. Juniors are the highest level credit earners in our group of focus, and so it is important to reevaluate the adjusted credit as noted in Chapter 5. This is our other view of credit loss, as we defined identity-based credit loss as pertaining to the specific course codes held by students and numeric loss as pertaining to the simple number associated with adjusted credit.

For each aspect of credit loss after transfer, *identity* or *numeric*, we show our broad experiences among the transfer students by Academic Level of Entry. Displayed in Table 6.6 is first the average transferable credit to help frame the average GCU credits, shown with the average proportion of GCU credits held post-translation and the average GCU credits total for reference. We saw the proportions spread earlier in Table 6.3 and expand upon it here, further defining the experience of credit loss. With GCU credits being previously unexplored in this dissertation, we reiterate that

Acad. Level of Entry	Avg. Transferable Credit	Avg. % GCU	Avg. GCU Credits Tot.	N
Freshman	19.0	44.8%	8.4	1,857
Sophomore	42.7	42.4%	17.9	3,220
Junior	66.6	38.3%	25.6	2,152
Total	43.7	41.8%	17.8	7,229

Table 6.6 Breakdown of GCU credits for transfer students by Academic Level of Entry, displaying the averages of incoming (transferable) credits, proportion of their incoming credits coded as GCU, and flat numeric GCU credits.

Acad. Level of Entry	Avg. Transferable Credit	Avg. Adjusted Credit Tot.	% Pop. With > 0 Adjusted	Avg. Adjusted Within Group	N
Freshman	19.0	0.1	2.6% (N=49)	5.1	1,857
Sophomore	42.7	0.2	4.0% (N=128)	4.2	3,220
Junior	66.6	7.2	65.2% (N=1,403)	11.1	2,152
Total	43.7	2.3	21.9% (N=1,580)	10.3	7,229

Table 6.7 Breakdown of adjusted credits for transfer students by Academic Level of Entry, displaying average transferable credit and adjusted credit for the total population, then the proportion of transfer students with non-zero adjusted credit & their average adjusted.

holding a non-zero amount of GCU credits is extremely common across all TYC transfer students in this analysis.

On average for Freshman transfers, 44.8% of their credits become GCU credits, though their average transferable credits is around 19.0 credits. For the lowest average of transferable credits, they have the highest proportion that become GCU credits, though this average amount is 8.4 held GCU credits. Sophomore transfers bring in more credits at a transferable average of 42.7 credits, while they have a slightly lower proportion of transferred credits becoming GCUs at 42.4%. This average is 17.9 GCU credits. Junior level transfers have 66.6 average transferable credits, but the lowest proportion of GCU credits at 38.3% of their credits. The average amount of held GCU credits is 25.6, as expected the highest average.

Table 6.7 describes the adjusted credit outlook, which was described as numeric credit loss.

This breakdown is also side-by-side with average transferable credit, which does not change from the prior table, for easier reference. There is a total average of 2.3 adjusted credits among all TYC transfers. We see the highest amount of adjusted credits in Juniors with 7.2 adjusted credits, which is on par with the average amount of transferable credits being over 60 for Juniors. However, when we narrow down to view what proportion of each population holds a *non-zero* amount of transfer credit, we see that this proportion is heavily influenced by Juniors. 65.2% of Junior transfers experience some non-zero amount of adjusted credit, for which if we take the average of *that* population's adjusted credit, they have an average of 11.1 credits adjusted off. Freshman and Sophomore transfers both sit below 5% of their populations experiencing some non-zero amount of adjusted credit, both with around or less than 5 credits on average adjusted off respectively.

While we see a lesser percentage of GCU credits held on average in Juniors, we see that they are the group that is experiencing the grand majority of adjusted credits in all transfers. As we transition into viewing average time-to-degrees through credit loss, we can first display these various presences of credit loss and time-to-degree as an average. As described in the Refined Methods section, we view this descriptive as splitting the student group(s) as 'having or not having adjusted credit' as related to a zero or non-zero value to their adjusted credit, then a separate split of the students as being 'above or below 50% of held credits de-identified to GCU' per group. This gears toward defining the numeric and identity related credit loss respectively, as a first-pass attempt at seeing how we can differentiate between who does or does not experience credit loss and begins the next section.

6.7.2 RQ2: Effect of Credit Loss on Graduation Metrics

6.7.2.1 Effect on Time-to-Degree

We begin again with the breakdown through identity-based credit loss in Table 6.8. As established previously, the threshold for comparison lies in being above or below 50% of post-transfer credits being GCU credits. These separate populations bring out varying N, what with Junior-level transfer students having the fewest at 470 students and 21.8% of their respective population. Sophomores and Freshmen stand at 33.0% and 41.9% of their populations having more than 50% of

Acad. Level of Entry	% Pop. With > 50% GCU	Avg TTD for GCU prop. > 50%	Avg TTD for GCU prop. < 50%	Total Avg TTD	Effect Size
Freshman	41.9% (N=778)	3.4	3.4	3.4	0.05
Sophomore	33.0% (N=1,063)	3.7	3.7	3.7	−0.05
Junior	21.8% (N=470)	4.2	4.0	4.1	0.15^b
Total	32.0% (N=2,311)	3.7	3.7	3.7	-0.08^b

Table 6.8 The GCU population breakdown of students of which more than 50% of their transferred credits became GCU credits, enrollment TTD values for each population above and below this threshold, total average TTD in population, and Cohen's *d* for each Academic Level of transfer student.

Acad. Level of Entry	% Pop. With Adjusted Credit	Avg TTD for Pop. with Adjusted	Avg TTD for Pop. without Adjusted	Total Avg TTD	Effect Size
Freshman	2.6% (N=49)	3.6	3.4	3.4	0.37^a
Sophomore	4.0% (N=128)	3.8	3.7	3.7	0.14
Junior	65.2% (N=1,403)	4.2	3.8	4.1	0.50^c
Total	21.9% (N=1,580)	4.2	3.6	3.7	0.74^c

Table 6.9 The breakdown of adjusted credit populations, showing enrollment TTD values for each population who do or do not have adjusted credit, supplemented with total average TTD in population, and Cohen's d for each Academic Level of transfer student.

their credits becoming GCUs. We reintroduce time-to-degree here in the enrollment-based metric, which the average is taken for each group and then the averages compared through Cohen's *d*. For Freshmen and Sophomores, there are extremely small Cohen's d comparisons between their TTD measures. However, for Junior-level transfer students, there's an average of 4.2 years enrolled in the population with more than 50% GCU proportion, then an average of 4.0 years enrolled in the population with less than 50% GCU proportion. The Cohen's *d* effect size reports less than small for this comparison, with a significance of $p < 0.01$.

In Table 6.9, we see a similar breakdown with the previously defined groups of those with non-zero adjusted credit and those with zero adjusted credit. This time, the enrollment TTD measures contain more interesting results. Where Freshman-level transfer students have few

Acad. Level of Entry	% Pop. With > 50% GCU	Avg Excess for GCU prop. > 50%	Avg Excess for GCU prop. < 50%	Total Avg Excess	Effect Size
Freshman	41.9% (N=778)	5.7	6.0	5.9	−0.04
Sophomore	33.0% (N=1,063)	8.1	8.5	8.4	−0.04
Junior	21.8% (N=470)	14.1	10.5	11.3	0.28^c
Total	32.0% (N=2,311)	8.5	8.7	8.6	−0.01

Table 6.10 The GCU population breakdown of students of which more than 50% of their transferred credits became GCU credits, excess graduating credit for each population above and below this threshold, total average excess credit in population, and Cohen's *d* for each Academic Level of transfer student.

students experiencing adjusted credit with 49 total cases, they report a TTD of 3.6 years as compared to a non-adjusted population average of 3.4 years, with a Cohen's *d* of 0.37. This effect is still small, but noticeably higher than the GCU reportings. Sophomore-level measures are not as noticeable of an effect difference. In Junior-level transfer students, we see the highest individual population difference. Those with adjusted credit hold a TTD average of 4.2 years, where those without adjusted credit hold an average of 3.8 years. This difference yields an effect size of 0.50 to significance, which meets the medium effect size threshold. As well, delving into the totals yields a higher-medium effect size with a total difference of 4.2 years in adjusted and 3.6 years in non-adjusted. However, this is noticeably carried by the Junior population, as they are the grand majority of those with adjusted credit, meaning their average highly influences the total average TTD in that group, and vice versa for the total average of the other group.

6.7.2.2 Effect on Excess Graduating Credit

Carrying on into our other graduation metric, we unpack both the first reportings of excess credit per population and the total average excess credit in Table 6.10 for GCU population differences. Working with the same population of transfer students per Academic Level of Entry above or below 50% held GCU credits, we can first notice the spread of excess credits on graduation among them. Junior-level transfer students have an average of 11.3 excess credits on graduation, whereas Sophomores have 8.4 and Freshmen have 5.9 excess. We consider a short reference to the value of

Acad. Level of Entry	% Pop. With Adjusted Credit	Avg Excess for Pop. with Adjusted	Avg Excess for Pop. without Adjusted	Total Avg Excess	Effect Size
Freshman	2.6% (N=49)	8.3	5.8	5.9	0.27
Sophomore	4.0% (N=128)	6.7	8.5	8.4	−0.16
Junior	65.2% (N=1,403)	11.2	11.4	11.3	−0.01
Total	21.4% (N=1,669)	10.8	8.0	8.6	0.24^{c}

Table 6.11 The breakdown of adjusted credit populations, showing excess graduation credit values for each population who do or do not have adjusted credit, supplemented with total average excess in population, and Cohen's *d* for each Academic Level of transfer student.

total adjusted credits particularly in all Junior-level transfer students from Table 6.7, which shows an average adjusted on entry of 7.2 credits. The total average among all transfer students is 8.6 excess credits on graduation.

In the breakdown of the GCU proportion threshold, we see that only the Junior-level transfer student population has increased excess credits on graduation at 13.9 credits if looking at the group with more than 50% GCU proportion, whereas their below-threshold counterparts hold 10.5 excess credits. This results in the only significant Cohen's *d* effect size at 0.26, which is small to significance. Overall, comparing the other transfer student categories and the overall transfer population does not yield considerable effect sizes.

Table 6.11 shows the spread of excess credit for the separated adjusted credit groups. For the adjusted credit group, we recognize once more that Freshmen- and Sophomore-level transfer students do not have very high N in their populations of those who experience non-zero adjusted credit. Among each Academic Level of Entry, we see Juniors once again with the highest excess credit on graduation at 11.2 in those who experience adjusted credit. However, the average excess is slightly higher in Juniors *without* adjusted credit. As such, we see an interesting spread of effect sizes where Freshman-level transfer students have small effect size but to no significance, as well as the total population of transfer students to significance ($p < 0.001$), but not Sophomore- or Junior-level transfer students. It is noticeable that, considering how much of the adjusted population is in total represented by Juniors, that the difference in means is significant and to a small effect size in the total comparison. That is to say, we can still draw inference that Juniors are experiencing different graduation-level effects than Freshman-level or Sophomore-level transfer students in general.

6.7.2.3 ANOVA Results

With these prior results in mind, we expand with an ANOVA to help represent the general differences between the Freshman, Sophomore, and Junior populations. For each outcome of enrollment TTD and excess graduating credit, Tables 6.12 and 6.13 report pairwise *t*-tests to show both the general comparisons without separating the groups into adjusted and non-adjusted or GCU proportions, then each individual comparison between those groups.

In Table 6.12, few results manage to produce an eta-squared result greater than small. It is to be noted that for the portion of time-to-degree averages, *t*-test, and effect size, this information was already reported in Chapter 5 and therefore will not be reiterated. As we look to the separations of populations with less or greater than 50% of GCU credits held, we have large effect size in both enrollment TTD comparisons between Freshmen & Juniors with greater than *and* Freshmen & Juniors with less than 50% held credits. The Sophomore & Junior populations with greater than 50% GCUs have a medium effect size difference in TTD. Within excess graduating credit, a new comparison between populations shows not very significant effect size within the categories, though all of them are significantly different *except* the total comparison between transfers above and below the threshold. There are mostly small effect sizes within the remaining significant comparisons, with medium effect sizes in Junior-level transfer students above the threshold compared to both Freshmen & Sophomores above the threshold. These show interesting variances in Juniors with greater than 50% held GCUs compared to their peers in both enrollment TTD and excess graduating credit, which speaks to having more flat GCU credits held on transfer affecting graduation metrics.

Table 6.13 breaks down the groups of students by whether they do or do not have adjusted credits. It is important to note as we report these results that the populations for Freshman- & Sophomore-level transfer students are much smaller than their comparison groups of students, which we bring to note that Junior-level transfer students are the largest representatives of the population with adjusted credits.

Table 6.12 The pairwise t-tests result comparing each Student type by Academic Level and grouped by the Proportion of Held GCU credits, showing effect sizes within each respective interaction on enrollment time-to-degree and graduating excess credit.

(TTD) Contrast	Proportion	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	eta-square
Proportion	-	> 50%	< 50%	3.7	0.8	3.7	0.8	-3.2	$p < 0.01$	0.00
Student Type	-	Freshman	Sophomore	3.4	0.6	3.7	0.7	-16.4	$p < 0.001$	0.05
Student Type	-	Freshman	Junior	3.4	0.6	4.1	0.9	-28.7	$p < 0.001$	0.16
Student Type	-	Sophomore	Junior	3.7	0.7	4.1	0.9	-16.1	$p < 0.001$	0.05
Proportion * Student Type	> 50%	Freshman	Sophomore	3.4	0.6	3.7	0.7	-8.6	$p < 0.001$	0.04
Proportion * Student Type	> 50%	Freshman	Junior	3.4	0.6	4.2	1.0	-15.4	$p < 0.001$	0.20
Proportion * Student Type	> 50%	Sophomore	Junior	3.7	0.7	4.2	1.0	-10.0	$p < 0.001$	0.09
Proportion * Student Type	< 50%	Freshman	Sophomore	3.4	0.6	3.7	0.7	-14.1	$p < 0.001$	0.06
Proportion * Student Type	< 50%	Freshman	Junior	3.4	0.6	4.0	0.9	-24.0	$p < 0.001$	0.16
Proportion * Student Type	< 50%	Sophomore	Junior	3.7	0.7	4.0	0.9	-2.6	$p < 0.001$	0.04
(Excess Credit) Contrast	Proportion	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	eta-square
Proportion	-	> 50%	< 50%	8.5	11.3	8.7	11.4	-0.5	$p > 0.05$	0.00
Student Type	-	Freshman	Sophomore	5.9	9.1	8.4	11.1	-8.7	$p < 0.001$	0.01
Student Type	-	Freshman	Junior	5.9	9.1	11.3	12.8	-15.5	$p < 0.001$	0.05
Student Type	-	Sophomore	Junior	8.4	11.1	11.3	12.8	-8.5	$p < 0.001$	0.01
Proportion * Student Type	> 50%	Freshman	Sophomore	5.7	9.0	8.1	10.8	-5.3	$p < 0.001$	0.01
Proportion * Student Type	> 50%	Freshman	Junior	5.7	9.0	14.1	13.7	-11.8	$p < 0.001$	0.13
Proportion * Student Type	> 50%	Sophomore	Junior	8.1	10.8	14.1	13.7	-8.3	$p < 0.001$	0.06
Proportion * Student Type	< 50%	Freshman	Sophomore	6.0	9.2	8.5	11.3	-6.8	$p < 0.001$	0.01
Proportion * Student Type	< 50%	Freshman	Junior	6.0	9.2	10.5	12.4	-10.8	$p < 0.001$	0.04
Proportion * Student Type	< 50%	Sophomore	Junior	8.5	11.3	10.5	12.4	-5.0	$p < 0.001$	0.01

Table 6.13 The pairwise t-tests result comparing each Student type by Academic Level and grouped by the status of Adjusted Credits, showing effect sizes within each respective interaction on enrollment time-to-degree and graduating excess credit.

(TTD) Contrast	Status	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	eta-square
Status	-	Adjusted	No Adjusted	4.2	0.9	3.6	0.7	23.0	$p < 0.001$	0.12
Student Type	-	Freshman	Sophomore	3.4	0.6	3.7	0.7	-16.5	$p < 0.001$	0.05
Student Type	-	Freshman	Junior	3.4	0.6	4.1	0.9	-28.7	$p < 0.001$	0.16
Student Type	-	Sophomore	Junior	3.7	0.7	4.1	0.9	-16.1	$p < 0.001$	0.05
Status * Student Type	Adjusted	Freshman	Sophomore	3.6	0.6	3.8	0.7	-1.8	$p > 0.05$	0.02
Status * Student Type	Adjusted	Freshman	Junior	3.6	0.6	4.2	0.9	-7.0	$p < 0.001$	0.11
Status * Student Type	Adjusted	Sophomore	Junior	3.8	0.7	4.2	0.9	-6.4	$p < 0.001$	0.06
Status * Student Type	No Adjusted	Freshman	Sophomore	3.4	0.6	3.7	0.7	-16.3	$p < 0.001$	0.05
Status * Student Type	No Adjusted	Freshman	Junior	3.4	0.6	3.8	0.8	-12.3	$p < 0.001$	0.08
Status * Student Type	No Adjusted	Sophomore	Junior	3.7	0.7	3.8	0.8	-2.9	$p < 0.001$	0.00
(Excess Credit) Contrast	Status	A	B	mean(A)	std(A)	mean(B)	std(B)	t-test	p-value	eta-square
Status	-	Adjusted	No Adjusted	10.5	12.6	8.0	10.9	7.8	$p < 0.001$	0.01
Student Type	-	Freshman	Sophomore	5.9	9.1	8.4	11.1	-8.7	$p < 0.001$	0.01
Student Type	-	Freshman	Junior	5.9	9.1	11.3	12.8	-15.5	$p < 0.001$	0.05
Student Type	-	Sophomore	Junior	8.4	11.1	11.3	12.8	-8.5	$p < 0.001$	0.01
Status * Student Type	Adjusted	Freshman	Sophomore	8.3	8.5	6.7	9.2	1.1	$p > 0.05$	0.01
Status * Student Type	Adjusted	Freshman	Junior	8.3	8.5	11.2	12.9	-2.3	$p > 0.05$	0.01
Status * Student Type	Adjusted	Sophomore	Junior	6.7	9.2	11.2	12.9	-5.2	$p < 0.001$	0.03
Status * Student Type	No Adjusted	Freshman	Sophomore	5.8	9.1	8.5	11.2	-9.0	$p < 0.001$	0.02
Status * Student Type	No Adjusted	Freshman	Junior	5.8	9.1	11.4	12.6	-10.9	$p < 0.001$	0.07
Status * Student Type	No Adjusted	Sophomore	Junior	8.5	11.2	11.4	12.6	-5.8	$p < 0.001$	0.02

This time, neither category of enrollment TTD nor graduating excess credit contrasts yield large effect sizes per contrast. However, most categories are significantly different from each other except for the Freshman & Sophomore adjusted populations in TTD and excess credit, as well as the Freshman & Junior populations of excess credit comparisons. For the remainder, there is medium effect size in the total adjusted to non-adjusted group TTD comparisons, which again is overrepresented in the former group by Junior-level transfer students. There is also medium effect size for Juniors to both Freshmen & Sophomores with adjusted credit in TTD, as well as Freshmen & Juniors without adjusted credit in both graduation metrics. In all, there are fewer individual comparisons between the academic levels per adjusted credit threshold, as the pairwise tests compare across the same adjusted thresholds, but as we view the total comparison, we see that the enrollment TTD and graduating excess credit averages are significantly different per adjusted or non-adjusted groups, though to medium and small effect sizes respectively, showing that excess credit generally varies less for the populations.

6.7.3 RQ3: Credit Loss for Physics Majors

Physics majors are looked at in an entry-level basis of whether they are a Physics major upon articulation to MSU. There are 85 students total in this category, and we will explore later how many of them graduate with a Physics degree. The methods of analyzing these Physics majors comes down to the low N of the group, which hinders many statistical comparisons between sub-populations like Academic Level of Entry. However, more specific analysis into this small group of students allows us to look more closely at how many incoming courses these students have in specific relevant subjects (e.g. Math or Physics) and how many GCUs are brought in from each of these subjects. This is done again with descriptive statistics, but allows for a closer look into specific curriculum and what may be some interesting results from courses brought in and our graduation metrics as defined.

Here we view the more specific makeup of GCU credits and basic descriptions of entering Physics majors' credits, credit loss, and graduation metrics. As we are viewing a small amount of students, 85 total starting as Physics majors and much fewer graduating with a Physics degree, we

Acad. Level of Entry	Avg. Transferable Credit	Avg. % GCU	Avg. Adjusted Credits Tot.	% Pop. With Adjusted	N
Freshman	20.6	42.2%	0.0	0.0% (N = 0)	9
Sophomore	45.6	40.1%	0.1	2.6% (N = 1)	39
Junior	67.1	34.7%	8.2	62.2% (N = 23)	37
Total	52.3	38.0%	3.6	28.2% (N = 24)	85

Table 6.14 Breakdown of credits for transfer students by Academic Level of Entry, displaying the averages of incoming (transferable) credits, proportion of their incoming credits coded as GCU, adjusted credit, and the proportion of students experiencing adjusted credit.

are working with too few N to reliably use many or any of our prior comparison tests.

First, we view the incoming credit amount, adjusted credit, percent of population that are experiencing non-zero adjusted credit, and proportion of incoming credits that are GCUs per Academic Level of Entry in Table 6.14. We find that we see similar outlooks of entry credit breakdowns as the broader population, with the Junior-level Physics entrants having 62.1% of their population experiencing adjusted credit, influencing the total average adjusted for these Juniors up to 8.2 credits adjusted off. Similarly to before as well, the average amount of GCU credits as a proportion of held credits on transfer decreases from Freshmen to Sophomores to Juniors respectively, though once again we note that the Junior population brings in an average amount of transferable credits of 67.1 credits.

Next, we view the total enrollment time-to-degree and excess graduating credits for this population, noting in an additional column how many of each of these categories graduated with a Physics degree, given that we are looking at Physics *entrants*. This is viewable in Table 6.15. In these graduation metrics, total average enrollment time-to-degree exceeds 4 years, especially for Junior-level transfer students who graduate in 4.4 years. As well, the average excess credits is similarly high, with 8.3 excess for Freshmen, 14.8 for Sophomores, and 18.1 for Juniors. The latter two groups, therefore, a full-time term or more in excess credits on graduation. As well, we see that almost half of the incoming Physics students ended up graduating with some type of degree from the College of Engineering instead of Physics, whereas only about 15% of Physics entrants

Table 6.15 Breakdown of TYC transfer graduation metrics by Academic Level of Entry, displaying the averages of enrollment time-to-degree, excess credit on graduation, and the number of Physics entrants who graduated with either Physics degrees or Engineering degrees.

Acad. Level of Entry	Enrollment TTD	Excess Credit	N Graduating Physics	N Graduating Engineering	N Total
Freshman	3.8	8.3	3	1	9
Sophomore	4.2	14.8	4	18	39
Junior	4.4	18.1	6	20	37
Total	4.2	15.6	13	39	85

Table 6.16 Breakdown of TYC transfer entry courses by subject and code, where relevant subjects are identified and the proportion of all courses brought in by Physics students are assessed for prevalence of subject and what proportion of those credits per subject are GCU.

Subject	Total Proportion	Proportion GCU
Math	20.8%	36.9%
Chemistry	8.3%	15.3%
Physics	6.3%	1.8%
Biology	3.9%	32.4%
Engineering	3.2%	70.2%
Other	57.0%	44.6%

graduated with a Physics degree after transfer from a TYC. The remainder graduate with a different degree.

We next view the specific GCU makeup in terms of relevant subjects to the Physics degree, which include any STEM courses, specific required courses, or Engineering credits, which we separate from other STEM considerations because of the general tendency at MSU for there to be overlapping interest between being a Physics major and being in the College of Engineering. We view the proportion of all courses brought in by these students broken down by each relevant subject, then whether the specific course code became GCU by proportion within the subject in Table 6.16. The specific courses brought in by Physics entrants, when looking at all courses brought in by each student, mostly comprises of Math credits (20.8% of all incoming courses). Math credits are extremely important as pre- and co-requisite courses for most STEM-related curriculum at MSU. The proportion of these incoming Math credits that come as GCUs is 36.9%, one of the highest proportions of the rest of the subjects. Of all courses brought in by these entrants, 6.3% are Physics courses, where we think back to how many of these students ended up graduating with Engineering degrees. However, the amount of Engineering courses brought in makes up only 3.2% of the incoming courses. Respectively, Physics and Engineering courses brought in come as 1.8% GCU and 70.2% GCU, which makes the prospect of many of these students graduating in Engineering rather interesting. For all other non-relevant courses to Physics curriculum requirements, 57% of courses are of other subjects and 44.6% of those credits come as GCUs.

6.8 Discussion

TYC transfer students transferring to MSU experience credit loss in adjusted credit up to a full term's worth of credit, while experiencing almost half of their credits losing identity in the form of GCU credits on transfer. While adjusted credit and GCU credits become nebulous after transfer in that a student can advocate and negotiate which credits apply to their graduation major, this is a barrier for transfer students having to navigate this transition without support.

It is important to recognize prior mitigation recommendations as connected to our particular interest in credit loss within and around Junior-level transfer students, and each has its own limitations: forming articulation agreements, which often exist between specific majors or departments for easier understanding of one-to-one translation and requirements and result in thousands of agreements between any two potential institutions; non-articulation programs such as transfer/-credit/Associate's programs, which can lay out suggested plans for students to follow but may not adhere best to all possible majors, making them selective; data sharing agreements between institutions, requiring communication between data teams at each institution and the resources to conduct research between each and every one of their partner institutions; informed advising for transfer at either institution, a resource intensive endeavor, requiring knowledge dependent on potentially many departments/colleges, as they may have to parse through tons of known resources; and again, early intervention to help the students solidify their pathways earlier, which we have already identified as difficult to discern how early is too early to intervene.

The results above give us insight into how the 'maximum allowed transfer credits' policy influences the type of credit loss that community college students experience during the transfer process and, in turn, how credit loss gives a window of insight in impacting TTD. While adjusted credit may be how many credits are lost on average, credit identity loss in the form of GCU credits adds perspective of what barriers community college students navigate upon transferring to a Bachelor's Degree Granting Institution. This policy bears financial implications for community college transfer students given the frequency and prevalence of lost credit.

Additional results around TTD and students with or without adjusted credit loss shows interesting time increases for TYC transfer students losing credit. The view from our results inquires on how students may be encountering increased TTD and adds further inquiry around financial aspects of enrollment. There are high expectations on community college students to correctly navigate transfer policy rather than on the institution to reflect on evidence and inform an iteration of the policy. Institutions can implement other policies or programs to make the transfer process for community college students more efficient and less of a financial burden, which may then impact credit navigation and enrollment time-to-degree.

TYC transfer students transferring to MSU experience credit loss in adjusted credit up to a full term's worth of credit, while generally experiencing almost half of their credits losing identity in the form of GCU credits on transfer. Looking further into Junior-level students elucidates on specific differences in separated groups of a) students with or without adjusted credit and b) students who have more than or less than 50% of their incoming credits de-identified to GCUs. The instances of significant difference for Junior-level transfer students is evident in that they make up the highest proportion of students experiencing adjusted credit, our numeric credit loss, and as well they bear significant differences when compared to their peers on having more than 50% of their credits becoming GCUs. This is supported by the notion that, since they hold more credits in general coming in, if they are impacted by a high proportion of GCUs in their transferred credits, they have more *flat* credits being de-identified. These impacts are seen to significance and medium-to-large effect between Juniors & their peers in both time-to-degree and excess graduating credit for these students above 50% of their credits becoming GCUs. This gives Juniors nuance in how many credits they are able to bring in, how they are affected by credit loss compared to their peers, and therefore how these policies or translation of credits impact their graduation success metrics.

The results above give us insight into how the 'maximum allowed transfer credits' policy influences the type of credit loss that community college students experience during the transfer process and, in turn, how credit loss gives a window of insight in impacting graduation time and credit. While adjusted credit may be how many credits are lost on average, credit identity loss in the form of GCU credits adds perspective of what barriers community college students navigate upon transferring to a Bachelor's Degree Granting Institution. This policy bears financial implications for community college transfer students given the frequency and prevalence of lost credit.

Additional results around TTD and students with or without adjusted credit loss shows interesting time increases for community college students losing credit. The view from our results inquires on how students may be encountering increased TTD and adds further inquiry around financial aspects of enrollment. There are high expectations on community college students to correctly navigate transfer policy rather than on the institution to reflect on evidence and inform an iteration of the policy. Institutions can implement other policies or programs to make the transfer process for community college students more efficient and less of a financial burden, which may then impact credit navigation and Time-to-Degree.

6.8.1 An Additional Perspective through Finances

So far in this dissertation we have brought up financial argumentation as a foothold of the importance of this work. Why is that so? Part of research around the transfer student experience, in its growth over the years moving from deficit framing to externally-critical framing (i.e. "What can the institution(s) do"), we encounter the many hurdles, barriers, or helpful & supportive aspects of the transfer pathway. As we introduce this chapter's data theming around credit loss, we also recognize what the higher education institutions or culture may be responsible for on part of that loss. As we think on pieces of transfer like credit articulation and translation, we also take a firm step back into pure logistical thinking: what does it cost to be a part of higher education, and how much am I poised to lose on the pathway I decide?

Though our prior chapter focused on time-to-degree as a measurement, it is not wholly appropriate for approximating finances aside from timewise dedication to higher education in semesters, which is not how we measured time-to-degree. Therefore, while we later explore time-to-degree in potential effect with credit loss, financial estimators here will not rely on time as a factor of financial dedication nor loss estimations.

Credits themselves are incredibly easy to attribute a monetary value, as institutions are typically quite transparent about how much tuition costs in a per-credit manner. MSU is included in this,

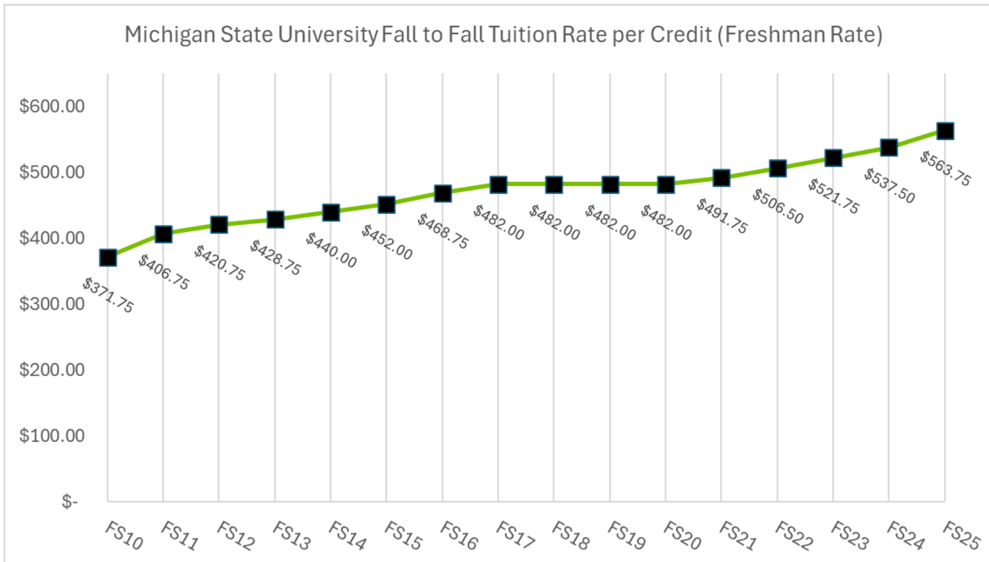


Figure 6.3 Year-to-year line chart of the progression of Freshman-rate tuition per-credit cost at Michigan State University from 2010 to 2025, where we see a general increase in per-credit cost.

though of course as time goes by, tuition costs change. In fact, since 2010, tuition cost per credit hour has increased at MSU almost year-to-year, except for a stint from 2016 to 2020 where the rate remained unchanged (Figure 6.3). Since Fall 2010 at MSU, the tuition has increased at an average increase of 3.11% per year at the Freshman rate cost. This comes with additional context that, at MSU, students of different academic levels will have different per-credit tuition cost that requires them to take out increasingly higher amounts of tuition at per-credit rate. Junior and Senior level students pay the most per-credit cost at the same rate, while Sophomores pay the next lowest, then followed by Freshmen. However there is no year-to-year comparison for every academic level rate, so the best possible estimate is the historically reported Freshman rate.

This is also with a caveat that in recent years, MSU has moved to block tuition. This began in 2019 in tandem with an initiative called ‘Go Green, Go 15’, which sought to increase graduation rates by encouraging students to take more credits per term earlier in their enrollment times. This is related to the concept we visited prior about early intervention for the purpose of targeting student success: that accruing *more* of something, whether it be ‘credit’ or ‘purpose of study’ or ‘knowledge of the higher education system’, early intervention is always a tactic that is particularly considered by institutions. Therefore here, the Go15 movement was interested in supporting students taking more credit per term in order to gain momentum in their pathways– and the movement was introduced conceptually in 2017, where the block tuition was actually implemented formally in 2019. Therefore, in tandem, there was encouragement overall to take more credit as an implication of graduating, and perhaps graduating 'on time'.

Reactions at the time of the announcement included a short article published by a student currently enrolled at the time, who expressed a mathematical paradox with the decision as a) biased toward students who have the time out of their week to take fifteen or more credits (i.e. students without full-time jobs) and b) only saving about two thousand dollars with a one-year graduation difference (moving from 12 credits per term to 15 credits per term); this latter point is spotlighted with the fact that the two thousand dollar difference is at an at-the-time rate of around sixty thousand dollars in total tuition [114].

MSU clearly acknowledges credit accrual as an indicator of timely graduation, yet we still encounter extremely strong hurdles that are hard to address, namely the 60 credit transfer limit, in which some amount of credit MUST be inapplicable, even if the inapplicable credit is loosely defined, which we will explore in defining credit loss. In all, the Go15 movement represents how the institutional view of time-to-degree typically shapes up, at least at MSU: while it is not as prevalent of a metric as graduation rate, it is still tied to some sort of financial representation of dedication in that block tuition is implied to help achieve timely graduation, at their decided cost.

Costs are rising. Recognizing that this dissertation typically covers *enrollment* years of 2010-2016 but allows for graduation up to 2025, the average cost among these years over all data in Figure 6.3 is $471.13 per credit. In short comparison to far-historic rates, MSU charged $114.25 in 1992 when they transitioned to semesters instead of quarters. We might consider more national trends in order to further contextualize the importance of financial dedication to higher education, such as Figure 6.4.

This perspective takes us temporarily out of the headspace of a single institution and into the typicalities of taking out loans in order to attend college. That is, to buy in to the per-credit tuition cost, one may take out loans, namely federal student loans in order to pay the cost. Not only is the

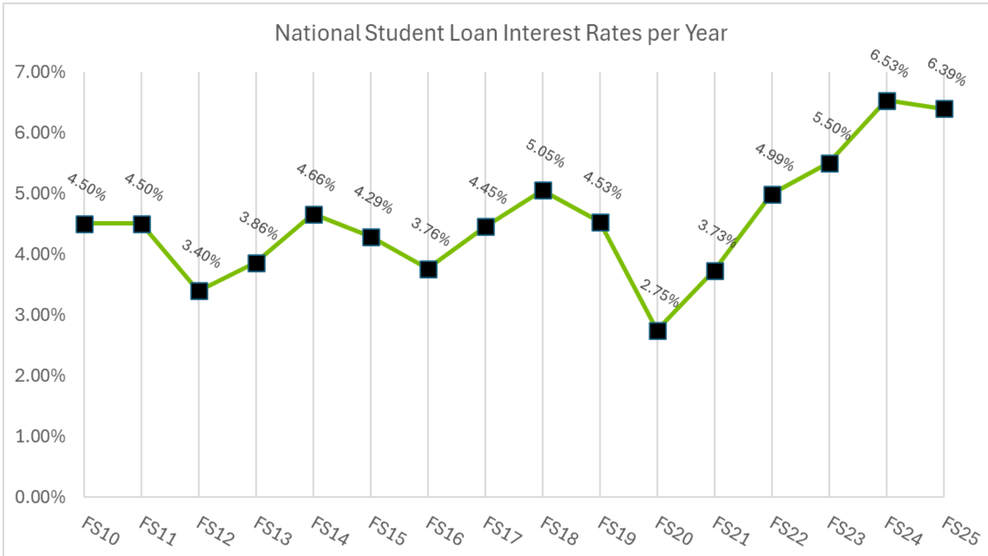


Figure 6.4 Year-to-year student loan interest rates, USA from 2010 to 2025, where interest rates generally increase during this period.

base cost rising, but the *interest rate* of the most common mode of paying tuition is also generally increasing, albeit more sporadically than the prior metric. The most recent rates have surpassed 6%. Interest rates are just one way to represent the slippery slope of financial dedication; not only is a student locking in to the rules of the institution, but as well subjecting themselves to normalized standards of how to actually pay for it. Time-to-degree, then, comes as an afterthought to cost. We will revisit these financial themes along this chapter as we view credit loss and time-to-degree in tandem.

6.9 Limitations

After cleaning this data, there were 20 students in the final population which had fewer than 120 credits on graduation. We presumed this a limitation related to something we could not measure or identify and opted to represent the excess credit accumulated as 0 excess credits. Other data cleaning limitations related to combining the Clearinghouse data and post-transfer MSU credit information for specific credits held, as this resulted in a dozen removed students. This error speaks to limitations around how combining thematically related datasets, but from differing sources, may result in missing or inconsistent data between them. As we join several views of data, missingness is often approached for removal rather than treating the source for why the data is missing.

This chapter is limited once more by the number of students within the study, as well as introducing course-level data, which is approached through MSU's collected data within the MSUEDW. Credit owned is a sum of total incoming credit, which is then combined in a subtraction with the adjusted credit amount determined as its own sum. Most adjusted credit takes place on students' initial term of enrollment at MSU, though there can be more credits adjusted off later for various reasons. In measuring total credit and credit loss, there is a clear distinction between Junior level transfers and Freshman or Sophomore level transfers, as Junior level transfers are the primary group interacting with the 60 credit transfer limit at MSU. Adjusted credit, as the determinant of the number of 'lost' credit, is generally not a normal distribution.

Where we break up credit into two aspects that we can — numeric and identity — we still cannot hit all the nuances of owning and losing credit. For us, it's about the power of this data access, that MSU does care to track what the identities of the credits used to be to the extent that we are able to see all courses in students' repertoire beforehand and then what institutions they are from, what they turn into, and whether they become blank (general) or potentially-applicable (coded) credit. We have that distinction, yet transfer students still encounter their credits losing power once inside a classroom and discovering they might have already experienced the course contents.

6.10 Conclusion & Broader Implications

Previous studies offer a slew of recommendations for aiding and abating the effects of credit loss [7, 30, 33, 110–112]. However, few study the effects of credit loss on various success metrics [110–112]. As we connect our principles of exploration in this chapter to the framework we've established time and time again, we reflect on what we've specifically said about policy and success through this chapter. As we explored in our discussion, higher education is expensive, increasingly so over the years. Showcasing the 60 credit transfer limit as a policy that a) exists as a restriction to incoming credit that was already paid for and accrued and b) a connecting piece for Junior-level TYC transfer students to their success metrics bolsters the theme of financial dedication and harm of unchecked policies. Even so, this policy varies nationally, meaning there is more places for this work effort to explore [107]. Our recommendations in reassessing policy come through wondering about the credit translation process and how much of a 'Black Box' experience this is for transfer students, then subsequently advertising articulation agreements to aid accurate transfer of credit *and* calling for continuous reassessment of course translation accuracy between institutions.

We need more resources on both campuses dedicated to understanding where their transfer students come from, articulation agreements, major requirements and so likely specific staff dedicated per department or college, and therefore a deeper understanding within our structures to help students understand what they have and where it goes. As we find that Junior-level transfer students experience credit loss disproportionately from other transfer students, we wonder about the efficacy of building more supports for transferring more credit in a blind manner. If we encourage students to bring in more credits or of certain types for certain programs, we must take care to ensure these credits are translatable and applicable to their major pathways.

CHAPTER 7

REPRESENTING COURSE CONNECTIONS: ARE INCOMING STUDENTS WHERE THEY “SHOULD BE”?

7.1 Purpose of this Chapter

Quantitative studies around transfer students majoring in Physics are few and far between [3, 4, 115–119]. Within themes of transfer student success, programmatic-level studies may approach topics of graduation rates, pathways, GPA, or other metrics, especially in STEM majors for implications of ‘rigorous studies’ impacting success inherently [26, 53, 66, 120, 121]. The Physics major curriculum comprises of a combination of physics, mathematics, computation, and general education course requirements; transfer students enter into this pathway at certain academic levels based on credit status, and may expect to be in certain courses with their peers by the time they enter. This chapter explores Physics students in the year 2017 for a representation of what courses they are enrolled in at certain academic status, whether they are enrolled in courses ‘typical’ to their status, and implications of transfer within the scope of credit loss or articulation to the MSU Physics curriculum. With developing a Network plot from this data in a visualization tool called Gephi, our results analyze common course enrollments, in our case seeing how many Junior-level Physics students are enrolled in Physics or non-Physics courses. We find that there is an interesting dynamic of transfer students enrolled in Engineering courses at this level and often graduating outside of Physics, which simultaneously glimpses into what counts as ‘Junior-level’ coursework, progress toward graduation in the Physics department at MSU, and implications around local policy supported by narrower analysis methods.

7.2 Introduction

This chapter refines the centering of the Physics curriculum, utilizing Network Analysis, and connections to our framework of challenging policy through the generation and researching of new ideas. This allows us to view connections to existing research using Network Analysis while continuing the conversation built in this dissertation through the lens of Physics majors as a part of STEM curriculum.

When we consider representing student connections, we must consider what the data stores and is able to tell us. This is partly attributable as a limitation, but more in terms of availability through what MSU stores and shares within its data warehouse. For example, a typical limitation would be how sex/gender are polled and labeled within the system and then whether the distinction is representative of student identity. However, forming connections is rather subjective. What construes a 'connection', let alone one that is of significance to the student? One might consider being in the same organization, club, or major a line of similarity, but MSU does not keep track of which clubs or organizations students are involved with in MSUEDW data. We do know what major students are, so if we continue with the caveat of trying to understand TYC transfer student connections more, we can shift our questions to reflect, how 'connected' TYC transfer students are to Physics curriculum and how we can choose to represent this connection, immersion, and termination at MSU.

7.3 Refined Background

This chapter stands out from the others in how its analysis is shaped and the methods chosen, but as well looking within a single discipline, which changes the methodology choices. Looking within a STEM major adds an additional strand of inquiry in literature that aids the choice of Physics in particular, then grounded by growing work within the field of Physics Education Research. The pathway through STEM up to graduation lies a groundwork for narrowing in to PER studies.

7.3.1 Pathways to Graduation in STEM

The framing of one's pathway is a strong part of current efforts in STEM research toward understanding why students leave, or conversely, why they may not be retained [61, 120–125]. The discussion around choosing to leave is especially bolstered by Seymour *et al.*'s *Talking about Leaving*, going into detail about the tendencies within STEM of leaving or staying, measuring these tendencies, and visiting several areas of potential reason such as the decision around major, high school preparation, classroom styles, belonging, and other topics that all shape the decision of persistence [121, 122]. Aiken *et al.* discuss modeling student pathways in Physics specifically, such that understanding the 'pathway' as a conflation of retention through the curriculum up to and through certain key courses, namely the Modern Physics course at MSU [119]. That is, evaluation of pathways often comes as a piece of persistence through majors, which other recent research efforts view through post-interaction of their courses of interest, rather than courses that may be commonly taken [126, 127].

Discussing pathways to graduation becomes increasingly important through STEM and locally, as made evident by Monsalve *et al.* who assess this with regard to students of color with transfer credits, finding that through STEM majors, the presence of more transferred credit from two-year colleges results in a significantly higher percentage of conferred STEM degrees than those without any transfer credit from two-year colleges and graduate from MSU [115]. This revelation supports not only the importance of transfer credit toward STEM graduation, but recognizing that transfer students experience interesting successes through higher education, and local policy and success analytics can begin the conversation around who transfer students are and what they are really experiencing in their pathways.

Supporting transfer pathways in STEM, looking locally at MSU's Physics Education Research efforts once again, is bolstered by the work of Cosby, Sawtelle, Dachille, and Rojas-Montoya [116–118]. The curation of tools, programs, and spaces to aid the transition of transfer students from their community colleges to MSU is varied among these three studies, beginning with the efforts of the Transfer Advocacy Group, which aids the transition of transfer students into MSU via a space of discussion formed by the students and transfer advocates [118]. The Lunch & Learn portion of a larger community college STEM scholars program aims to aid student retention by supporting transfer-intending STEM students and to understand their experiences [116]. Further work seeks to qualitatively represent and understand TYC transfer student trajectories through a receptive culture and the development of a transfer grid as an interviewing tool to understand these trajectories [117]. Each of these efforts are the rare work that comprise current efforts to understand TYC transfer student pathways, alongside some prior mentioned broader studies [54, 67, 98, 101, 102, 128].

7.3.2 Physics Transfer Foundation

STEM transfer studies and analytics are quite broad, including STEM-centric studies in the realm of student success performing comparisons to Non-STEM majors, viewing pathways both traditional and unique through majors, and introducing demographics-based studies to STEM transfer [26, 50, 52–54, 61, 127, 129]. As we narrow into transfer research, Physics-centric research narrows considerably. There has been recent considerable effort in recent years to bolster transfer analytics, for example reflecting on local TYC transfers and bridge connections with TYC Physics programs [15, 22, 25, 65]. Work from Myers showcases transfer students' self-efficacy at MSU utilizing an Experience Sampling Method of surveying self-efficacy multiple times per day, which is an excellent display of generating new inquiry through the means of generating new data that may relate to transfer pathways [130, 131]. Reiterating the need, then, for reporting from the American Institute of Physics to establish prior efforts of Physics transfer-related studies, we emphasize the need for more research in this realm [3, 4, 21, 65]. STEM studies recognize the richness of the transfer student body, and as such does the field of Physics. Thus, we look instead toward what PER *has* unfolded a basis for: Network Analysis.

7.3.3 Network Analysis

Network Analysis is a tool of practice commonly associated with the Social Sciences, then often called Social Network Analysis [132]. This is especially relevant to and around classroom spaces, which Grunspan *et al.* comment on in regards to student success analytics:

> *"Network analysis entails two broad classes of hypotheses: those that seek to understand what influences the formation of relational ties in a given population (e.g., having the same major, having relational partners in common), and those that consider the influence that the structure of ties has on shaping outcomes, at either the individual level (e.g., grade point average [GPA] or socioeconomic status) or the population level (e.g., graduation rates or retention in science, technology, engineering, and mathematics [STEM] disciplines)."* (pg. 167).

The analysis method relies on the visual. With many other plots like line plots, scatter plots, and even to some extent regression, it is merely supplementary what the visual provides to otherwise mathematic or summary descriptive results. With network plots, the visual *is* the story, so it becomes nigh impossible to summarize without the visual alongside it. Imagine an example of representing student connections through having clubs in common. You might state a result of 'students are less connected when they don't have clubs in common', but then getting into specific detail loses nuance— which students, how many clubs, which clubs, what is a strong connection, how centralized is it to a certain club or person? There is already much nuance that network analysis can extrapolate on, but the Network Plot aids all of these supplementary questions with shape, color, line type, and various other means.

In direct relevance to student success, that Network Analysis is regarded as a tool to address these types of hypotheses implies its merit as a means of answering questions or generating inquiry for the fields respective to these topics. Froehlich et al. describe Social Network Analysis throughout Education Research as in need of quantitative and qualitative cohesion rather than overreliance on quantitative-exclusive themes [133]. Grunspan *et al.* mention PER in particular connection with Eric Brewe's itinerary of work regarding performance and interaction outcomes, this itinerary expands out to the works of Zwolak et al. for persistence and interaction analysis through networks, self-efficacy through Dou *et al.*, engagement and academic performance through Williams *et al.*, performance from Bruun and Brewe, and work from Adrienne Traxler on broadstroke PER networks with gender analytics [134–139].

As established, these various realms of Network Analysis, whether inward to the PER field or outside of it, often rely on mathematic representation to fully communicate an outcome, effect, or impact statement about the inner machinations of education spaces. When pivoted toward Institutional Research, the question must begin again at what the Network plot is *for*. Portraying connections between students can be valuable, but little does IR reach hyperspecific classroom spaces as analytic vehicles. They are researching for a whole institution. As such, we re-pivot in a more middle-ground lane between PER and IR: the Department of Physics & Astronomy at MSU.

Before delving into that specific realm, the summary of ending up at the departmental level is the mesh of where we can reasonably return to our framework that supports data-driven policy. Where our flow through policy, metrics of success, and inquiry drives us ends up back in the realm of policy and what we can reasonably tackle institutionally. The broad realm of institutional policy is quite large, but a department's policy is much smaller, considering we can look closer at implications of post-credit translation nuances of enrollment. With that, we return to the framework.

7.3.4 Connection to our Data-Driven Policy Framework

As we round out the data analysis of this dissertation, the framework we cultivated around data-driven policy has been addressed in a success metric (time-to-degree), in direct policy (credit loss), and now we push to the theoretical 'last stage' before re-addressing existing policy: curating new inquiry. This stage, as described in the framework chapter, is one which has many considerable paths of exploration. The purpose of this stage is to tie together what we know of existing or implementing policy, how and with which metrics we have evaluated student success, and then to an open-ended curiosity. What is going on within students? Outside of simple success metrics? What does it mean to address policy with our themes and where do we push the boundaries of historic policy or programmatic change? However, we should take an additional step back and review the whole framework as a story of our analysis thus far.

7.3.4.1 Previous Chapters: Policy and Success Metrics

Where Chapters 5 and 6 lived in tandem with each other in terms of data accessing, acquisition, and curation, they still aimed for different parts of the framework. Our use of Python, descriptive statistics, regression, ANOVA, and closer looks so far aimed to understand how certain aspects of transfer pathways are clouded by policy/metrics he hold those pathways to. Our framework as a whole says: when we evaluate transfer students, we notice, sometimes all at once, the whole flow of policy through to success metrics through to inquiries. It's a whole song-and-dance, not particularly separated. We understand once again *why* this framework was established in the way we built it. Students will always remark about something about the institutional experience not working, and in response, institutions focus on what they chose to do rather than remarking about how they might have listened. This framework serves as more of a conversation from institutions. Students should ask, ‘what *are* you [the institution] assessing about me and where are your changes occurring?’ and institutions *should* be responding, ‘where are your recurring pains and how can we help?’

When the pains are policy oriented or rooted, it is difficult for institutions to *subtract* or *uproot*, which is why we often see suggestions of *additions*. Transfer programs, transfer advising, early intervention, articulation agreements, and data sharing agreements are all common recommendations from literature that are, in effect, additions to existing policy even after they might have critiqued that very policy by proxy of analysis. It is never outright recommended to reassess, change, or remove policy, in that much of the transfer related policy is deeply integrated into the systems of transfer and higher education expectations.

This framework, thus far then, has taken this hesitation of knocking policy and reframes the approach as a whole. If you change the way you analyze success (what are your metrics, how are they measured, how do you define credits and loss) and you see the pains (differences in time-to-degree, means of credit loss occurring, financial implications), you might be closer to the reason why calling out the policies is necessary and where you might begin looking *for* change. *Do* articulation agreements work, or do we have a need to reassess the transfer credit translation system as a whole to ensure credits are being transferred as experienced from institution to institution with an updated perspective? We can focus more on how to avoid an extreme amount of GCUs/deidentified credit, have less excess credit on graduation, and have more care in the transfer credit accrual process where interacting with the 60 credit transfer limit becomes less of a harsh commonality. And this care can be taken for any particular policy, not just those we’ve targeted or named in this dissertation.

As such, policies are spoken about more commonly through success metrics nowadays, as we’ve noticed before [33, 71–74]. Since this process doesn’t result in policies being uprooted or changed, we should be freer to scrutinize *why* those policies are in place. *Why* do we have a 60 credit transfer limit? Some might say it ensures the merit of earning a degree from the destination institution to have to earn the remainder credits to 120 to graduate. But what else is it for? Or rather, what else does it *do?* It is relatively confusing to navigate and raises a lot of questions about *which* credits, why *these* credits, and how do I keep my credits on part of the translation effort. Chapters 5 and 6 saw us viewing enrollment time-to-degree and looking closer into credit loss at MSU, both validating transfer experience and challenging the perspectives of success as established by the continued policy influence. Chapter 5 was framed as being in the success metrics box of our framework, and Chapter 6 as the policy box in interaction with success metrics. Chapter 7, then, naturally bloomed in the remainder of these initial analyses. Where else can we look and inquire, and as we shift analysis what lenses can we use to perform analysis?

7.3.4.2 The Inquiry Box

The whole point of the flow dialogue of our framework is to recognize a goal of reassessment at *some point in time*. In a cyclical nature, the afterword of assessing success should be to ask more about what's going on and how we might fix, address, or even pinpoint anything that can be done at all when we notice pains or interesting phenomena. This often leads to what else we can look at, or where we can feasibly start asking additional questions. Institution-wide policy change at a 50,000+ student enrolling R1 institution is an extremely big tackle. One of our motivations, then, is to look more locally, hence our point of view shifting to a smaller population of Physics students. More local assessment can be a better opportunity to think of more local assessment for change.

7.3.4.3 Inquiry of Physics Course Pathways at MSU

Evaluating course enrollment upon a certain status at MSU can be a way to showcase whether transfer students are taking the same courses as their peers– though not particularly implying that these are the 'right' courses to be in. This nuance distinguishes what is 'right' from what is 'typical', considering the representation of FTIACs in Physics highly outweighs the transfer population.

Thus, the Network analysis pushes away from typical metrics of success and more into new inquiry of the importance of being in the same courses as your peers. If you are a Junior transfer student in credits, should you be actually expected to be in the same courses as your Junior FTIAC peers, or is this a presumption that cannot be reasonably met? If not, would suggestions such as articulation agreements or reduced credit loss increase the likelihood of being in the 'typical'

The schedule below shows a sequence for completing required courses for the students who major in a **Physics B.S. (120 credits)**.
Variations and substitutions are possible.

Freshman Year			
Fall		Spring	
MTH 132	3	MTH 133	4
PHY 183 or PHY 193H *Fall*	4	PHY 184 or PHY 294H *Spring*	4
CEM 141	4	CMSE 201 (Python)	4
WRA 101	4	CEM 142	3
		CEM 161 lab	1
Total	~15	Total	~16

Sophomore Year			
Fall		Spring	
MTH 234	4	MTH 235	3
PHY 215	3	PHY 321	3
PHY 191 lab *Fall*	1	PHY 192 lab *Spring*	1
IAH 201-210	4	ISS 2xx level	4
Elective	3	Elective	5
Total	~15	Total	~16

Junior Year			
Fall		Spring	
*PHY 415 *Fall*	4	PHY 431 lab *Spring* (or PHY 440 lab Fall)	3
PHY 471 *Fall*	3	PHY 410 *Spring*	3
ISS 3xx	4	*MTH 314	3
PHY 440 lab *Fall* (or PHY 431 Spring)	4	Biological Science	3
		Elective	3
Total	~15	Total	12-15

Senior Year			
Fall		Spring	
Capstone course	3	Capstone course	3
PHY 481 *Fall*	3	PHY 472 *(Elective) Spring*	3
PHY 451 lab	3	PHY 482 *(Elective) Spring*	3
IAH 211+	4	Electives	3
Elective	2	Electives	4
Total	~15	Total	~16

Capstone Courses: Complete 2 of 4 courses listed below
PHY 491 - Intro to Condensed Matter Physics - Fall Only
PHY 492 - Intro to Nuclear Physics - Spring Only
PHY 493 - Intro to Elementary Particle Physics - Spring Only
PHY 494 - Survey of Physics Education Research - Fall ODD Years Only

Upper Division MTH Requirement, 6 credits:
* = MTH 3xx or MTH 4xx
Electives to Reach 120 credits, ~20 credits:
Recommended for Grad School: PHY 472 & 482
College of Natural Science Sample Elective List

University Required Courses, 23 - 24 credits:
WRA 101 (1 course) ISS (2 courses) IAH (2 courses) &
Biological Science (1 course)
Recommended: IBIO 150, PLB 105, ENT 205
Other BioSci recommended: ISB 201, ISB 202 & ISB 204
Other Options: MGI 141, MGI 201, PSL 250, BS 161

Figure 7.1 The Department of Physics & Astronomy at Michigan State University provides a sample schedule for four years of fulfilling Physics major requirements.

courses? Where *are* Junior transfers in Physics in their course pathways? This interacts with a more local policy in the department of Physics & Astronomy, targeting enrollment dynamics around the Physics curriculum these students may be expected to be in. See Figure 7.1.

Assessing transfer pathways considering specific curriculum is not unfounded [128]. The purpose may typically be to assess navigational errors, barriers, or interesting aspects of coursetaking along the way to graduation within that major, or perhaps in STEM [53, 54, 115]. In focusing heavily on Physics students, we are highly interested in the courses they are enrolled in, but as well what it means to be enrolled in those courses at a specific student level. We have provided interest in the realm of being a Junior with our results from the other chapters (e.g. how they interact with credit loss and time-to-degree), but one aspect we've rarely explored is post-transfer dynamics with regard to course taking *at* MSU. Figure 7.1 supplements dialogue on what courses are a) needed to graduate from MSU with a Physics BS degree, and are b) sorted in a *recommended* working pathway to timely graduation. This is not a requirement, and therefore not an explicit policy, but it is given as a guiding example for students to see pre- and co-requisites satisfied such that the Physics-specific curriculum may be tackled in four years. This gives implications around preparation and a careful eye on credit translation as to what courses might be targeted as very important to take 'in time' for Junior status.

The sample schedule is particularly interesting as it also elucidates a pattern of when courses are available, if they cycle through less often, as well as general requirements for the University and when those may be best fulfilled. We find particular interest among, of course, the Junior Year section wherein the sample student has already satisfied three levels of Calculus plus Differential Equations, all introductory Physics courses, and some of the general University required courses. Math plays an extremely important role for the Junior and Senior Year course sections. Specifically, Calculus III (MTH 234) and Differential Equations (MTH 235) are pre- or co-requisites for *all* of the Physics courses in the last two years, yet they are assigned as *pre-requisites* as an implication that satisfying the credit as early as possible is recommended. We will describe more about these requirements in our methods section.

7.4 Research Questions

Before firmly diving in to the methods of this chapter, we establish the Research Questions of our analysis inquiries:

1. How might we use IR databases to represent course connections?
2. In Physics students, how are we able to show the courses students are in and determine if they are with their fellow 'cohort' of FTIACs and transfer students in similar courses, in the 'right' courses to be on track to graduate, or graduating with a Physics degree?

As this chapter unfolds, we recognize it as a two-fold piece of new inquiry in data-driven policy; what data *is* kept and by what means is it assessable by IR methods and considerations toward Network Analysis as a tool within IR, and then assessing the outputs of the developed Network plots for seeing what the output can show through our tools *and* what we consider analytical results of our data-driven inquiry. As an exploratory chapter, we have a lot of freedom in forming our Network Analysis as for shaping what it can service. Whether we want to know current or historic enrollments, graduation status, shared courses, or other inquiries, we have freedoms limited only by the tools we are choosing through Gephi and Tableau.

7.5 Refined Methods

7.5.1 Sample

The Network analysis and data pull were performed mostly in Tableau and Gephi [87, 88]. We deviate away from Python for this chapter as Tableau and Gephi's Network visualizations are intuitive to navigate and perfect for exploratory analysis. We utilize SQL for pulling data as similar to Chapters 5 and 6, though this time we are unconstrained from needing data from the National Student Clearinghouse or general time-to-degree related SQL pulls, such as information about time spent prior to MSU or translation-based transfer credit information [80]. To access data, we used Tableau, which is able to connect directly to the MSUEDW and pull data as designed in SQL pulls. The other chapters of this dissertation relied on forming separated queries in order to navigate hardware limitations of performing a singular huge pull of data — millions of rows of data spanning the enrollment range of 2010-2016 — and joining them post-individual paring and cleaning. Here, we only need to access information regarding Physics majors, making the potential data pull much smaller.

Accessing data through Tableau to query directly from the MSUEDW requires different structuring in that we perform joins *within* the pulls as possible or desired. Querying from the same source as the prior chapters keeps our data somewhat consistent, despite not considering all of the same variables as mentioned above. As a more direct method of connection, these pulls within Tableau are typically done in larger syntax with many datasets joined at once. However, there is still the ability to join separate SQL pulls if needed, of which we required two different accesses in order to form the whole dataset.

The construction of the data contains much of the same general syntax or variables as Chapters

Student Level	Graduation Status	N
FTIACs	Graduated, Physics	15
	Graduated, Non-Physics	16
	No Degree	6
Transfers	Graduated, Physics	5
	Graduated, Non-Physics	11
	No Degree	8
Total		61

Table 7.1 The population of students by graduation status through holding a Physics or Non-Physics degree, or no degree. Within transfer students, 5 immediately transferred from a 4-year institution and the remainder 19 transferred from a 2-year institution.

5 and 6, though the pulling itself has changed to reflect courses taken at MSU, Physics majors, and students enrolled specifically in the terms for the 2017 academic year. This choice of academic year is not meant to be influenced by the prior chapters aside from allowing several years post this time for graduation data to accrue. The choice of constructed data is, ideally, meant to inspire further lines of inquiry, such as how other academic year enrollment choices may influence connections or course enrollments, or inspiring the selection of other disciplines than Physics for curriculum navigation. For this analysis, students were eventually classified by the following: enrolled in those two terms of the academic year (FS17 and SS18), their respective academic levels *at the time of those terms*, then filtered for academic levels of interest. We are able to view which Transfer students are new or returning in these terms, whether they attended a two-year or four-year institution prior to transfer, and whether they are In-State attendees. The final SQL pulls are located in Appendix A. The specific makeup of the populations based on our demographic interests are in Table 7.1.

7.5.2 Further Evaluation of the Sample Schedule

While we do not inherently focus on the mechanics of navigating pre- and co-requisite courses with regard to taking courses ‘on time’, our focusing on Junior status brings into question what is encouraged by the department, or any department for other respective majors, on which courses might be best taken at a certain time beforehand or co-requisitely. Taking courses ‘on time’ can be viewed in Network Analysis through our setup of viewing where Junior-level students are *actually* enrolled and what courses, via the sample schedule, may be encouraged to be in by this point.

Therefore, it is worth exploring these pre- and co-requisites in more detail prior to analysis in that it aids defining why the Junior-status, and sometimes Senior-status courses are placed in the order that they are in the sample. The Physics courses required to graduate beyond introductory (100-level) courses are:

- PHY215 (Modern Physics)
- PHY321 (Classical Mechanics)
- PHY471 (Quantum Mechanics I)
- PHY440 OR PHY431 (Optics OR Circuits Lab)
- PHY410 (Statistical Mechanics)
- PHY481 (Electricity & Magnetism I)
- PHY451 (Advanced Lab)
- Various Capstone Physics courses

PHY 415 (Methods of Theoretical Physics) is not required to graduate, as a student can take a 300-level Math course instead. Capstone Physics courses are considered advanced courses and mostly tend to require upper-level Physics courses as pre-requisites, namely Quantum Mechanics I (PHY 471). While this is interesting, we may not particularly point out Junior enrollments in these courses as excellent markers toward graduation progress. The remainder of these courses all baseline require the introductory (100-level) Physics courses prior to enrollment, which is not surprising. PHY 215 (Modern) and PHY 321 (Classical Mechanics) are considered, as the next steps up from introductory, the next two common requirements of the 400-level courses. The Physics department does not require other 200- or 300-level courses, to note. The remaining 400-level courses are, then, typically interchangeable as to what order they can be taken, aside from two exceptions: PHY 410 (Statistical Mechanics) requires PHY 471 (Quantum Mechanics I), and

PHY 451 (Advanced Lab) requires either of PHY 440/PHY 431 (Optics/Circuits Lab). All of the 400-level courses require either MTH 234 or MTH 235 to be enrolled, either pre- or co-requisitely.

In review, Junior year can be quite a flexible ordeal. However, we intend to view in this study if a student is at Junior-level status in credits and is NOT enrolled in either some 400-level courses OR MTH 234/235 in order to take 400-level Physics courses. This, as bolstered by the sample schedule, is a marker of 'ample' progress toward graduation with a Physics BS degree for our time frame.

7.5.3 Data Construction for Gephi

Within Tableau, further manipulation of the data — outside of specific analytical tools used to shape the Network plot in Gephi, which will be explored in Results — is flexible wherein Tableau is extremely good at reshaping, recalculating, and forming new pieces of structured information to add to the bigger picture. Even if a broader range of students are to be selected from, Tableau is easy to filter through tables, such as defining your population by term, year, or academic level, and can calculate new fields/columns through further code called 'VizQL'. An example of the latter is how we redefine cell values that may be null to named values, like a lack of degree earned.

The specific filters we used were to provide information as closely related to the prior chapters of this dissertation as the data source is slightly different. We filtered for the term to be displayed, which will show courses these students are enrolled in for both Fall Semester 2017 and Spring Semester 2018 for the academic year of 2017. This year choice was decided in part by the addition of a filter for graduation status, as we wanted to provide a window of graduation time for 6 or more years to graduate in calendar years.

The graduation status filter was utilized differently than the previous chapters, as we used to only keep students who had graduated in order to calculate time-to-degree. Here, we designate a graduation status of 'No Degree', 'Graduated, Non-Physics', and 'Graduated, Physics' to distinguish those who earned a degree or did not, and whether the degree earned was Physics or Non-Physics. This latter designation can include any other degree and is not additionally filtered down to STEM or etc. related degree programs.

Our last piece we took note of was the institution type that the transfer students had last transferred from. Within the MSUEDW and through our SQL pulls, we are able to pull information about other institutions attended by the students, including if they went anywhere during or after MSU. This information is not as specific as the National Student Clearinghouse data which is able to give term-based attendance, but is still specific enough to give the type, name, and date range of the attended institution. We extrapolate the institution that was attended at the latest date up to enrollment at MSU and use that as the institution which they transferred from. As noted in Table 7.1, only five of our transfer students are from a four-year institution, while the remaining Juniors all transferred from a two-year institution, which are kept to retain as many transfer students as possible within this Physics discipline analysis. An additional reason for this decision is that, in post-credit translation dynamics, all transfer students are subjected to this translation process and individual institutions have widely varying translation accuracy. On viewing these five students who transferred from four-year institutions, there was no particular pattern of graduating with or without Physics degrees, nor being enrolled in particularly interesting courses except in alignment with the trends we will discuss in our results, and thus we keep them in this analysis alongisde the caveat that we can remove them from view manually any time.

As a last note for our demographic selection, we are only looking at Junior-level students enrolled in the academic year of 2017. This means that we are selecting those who are of Junior year academic status by credit in 2017, so they can hit Junior status in either that Fall or Spring term and be considered in the dataset. This also means that transfer students are not *particularly* entering as Juniors, and rather the population can be a combination of those entering that year as Juniors and those who entered in prior years at different statuses and have hit Junior status that year. This is an important distinction, as we are not making inferences about coming in as a Junior and assessing course status through that particular lens, which we would be interested in assessing in future studies.

Once students are selected, they are vetted for the courses they are enrolled in at the time. Courses are deemed important if directly relevant to Physics, Mathematics, or Engineering courses, and particularly the curriculum of earning the Physics degree. There are several courses that are required under the Physics major curriculum, such as general Arts & Humanities, Social Sciences, Biology, Chemistry, and Writing courses that are not considered in the lineup considering they are generally introductory courses and are recommended to be taken at the students' leisure, rather than during specific recommended academic levels.

We kept Engineering considering inquiry related to whether the Engineering discipline is a known stepping stone for incoming Physics transfer students to transition into at MSU. Retaining Engineering courses within the analysis allows us a perspective into whether this assessment follows with our distinguished levels of graduation (No Degree, Graduated, Non-Physics, and Graduated, Physics) and to assess if there is a visual interpretation of this phenomenon of Physics majors taking Engineering courses and what that may look like on a more granular level.

In Gephi, one can manually remove pieces of the Network plot from view, allowing us to customize the selection that is displayed as desired. However in the initial construction of the data, *all* courses that these students are enrolled in can and *should* be considered as potentially relevant in future uses of this type of analysis. Drawing every course for a given population from MSUEDW allows the analysis to have flexibility for the researcher's discernment in what they want to measure about pathways taken, majors enrolled, and anything that highlights desired construction of data for their particular research or articulation interests.

Our last points of data construction were relevant to the transfer-related variables such as the last institution attended prior to transfer, and then the graduation-level variables for all student types such as the degree earning status and the type of degree earned. These come from entirely separate source tables as the general student information. These are also both aspects of information that happen to be reformatted within Tableau, as we are supplied many specific results (e.g. majors of degree earned) that we can bin together for simpler presentation. Finalized formatting is done purposefully for the Gephi platform, which will be explained in the next section.

7.6 Analysis Methods

7.6.1 Network Analysis

Network analysis has many facets to it that people have pursued understanding connections for years. Measuring connection or choosing how to weigh connection are part of the process of facing the limitations of your data and the questions one is trying to answer. In our case, we are trying to represent transfer student pathways in that we can view where they are after they come to MSU and face physics coursework. Connectedness, in this realm, would relate implicitly to the 'correctness' of the pathway — we can view this in relation to two points, which are:

1. which courses they are in specifically and whether those courses are typical for their academic level of entry, and

2. whether the courses they are in at their entry level are similar to the courses being taken by FTIAC students at the same level as those transfer students.

For 1), there are courses that are colloquially known for being Freshman, Sophomore, Junior, or Senior level courses— especially courses that are pre-/co-requisites for later courses. As an example, PHY 481 is Electricity & Magnetism I and is commonly taken by Junior/Senior level students. It, however, only has Calculus III as a prerequisite. PHY 184 (introductory calculus-based Electricity & Magnetism) is commonly considered a Freshman level course and has Calculus II as a co-requisite requirement. For 2), since the first point is able to shift over the years with major requirement changes or what is truly "supposed" to be a certain level course, being where your peers are at is another sort of litmus test to what is that place in your pathway you should be. As an example here, if one enters as a Junior level transfer and their fellow peers who are Junior-level FTIAC students are all enrolled in PHY 481, that may set a precedent for that time period that that course may fulfill a sort of typicality-expectation for being at the on track to graduating.

Then, we think about what being on track to graduation actually means, and how a Network plot is designed to help answer this question. The point of showcasing connections with a Network plot is to understand what connection can tell you: who is connected with whom, or to what? In what frequency? Is there nuance to who starts the connection? There are slews of ways to say what a Network plot can communicate, but I will focus on a few that may relate to our interpretations of transfer students and their courses on attendance at MSU.

Network connections are often designated as *directed* or *undirected*, as in whether it matters that Student A started the connection to Student B, vice versa, or not at all. We work with *undirected* connections, or 'edges'. In the case of representing connections *between* students, we would consider the *weight* of that connection. With regard to our line of inquiry, one of our considerable questions is, how many courses do our students have in common in the selected time frame? This can represent a sort of typicality in that a Transfer or FTIAC should hopefully have courses in common if they are enrolled at the same time, in the same discipline, and are of the same academic level. Alternately, we have the option of adding courses as nodes, which would eliminate edges between students, and instead allow for us to see the specific courses taken by each student type. The weight of the edge then does not matter, as multiple nodes can be represented around a singular node, e.g. many course nodes for one student node, or many student nodes for one course.

We prefer the latter path, as adding specific courses bolsters the conversation around what courses are 'typical' per student in a considered window. Another aspect of Networks is *degree centrality*, which is a representation of the number of connections per node and is useful for interpreting 'importance' of a node [140, 141]. In the case of course enrollments, high centrality would imply an importance to that course; however, we also want to consider which are highly central for FTIACs or transfer students at this specific academic level. Viewing the commonest courses per group at Junior level will have implications in what courses all of these students are taking, when, and what requisites the seating of each student in those courses. FTIACs do not set the standard of course enrollment or 'taking X course at the right time', but there *are* suggestions that certain courses are *to be taken* at particular times, e.g. through explicit pre-/co-requisites, or through departmental suggestions.

7.6.2 Themes of Centrality

Course nodes are reflected on their centrality (e.g. how common the course is among students in the considered academic level(s)) then additionally for proportion makeup among their connections to students between Transfer & FTIACs and graduation status (e.g. graduating with a Physics degree, graduating without a Physics degree, or not graduating at all). For as few Physics students are in the representation, we aim to show a possibility in how these course connections can be represented in a legible and feasible manner, as Network Analysis is susceptible to over- or under-representing the intended message and research questions. While additional information about student demographics and school status are all interesting analytical drivers, not all of the information will be displayed in our representations. Per our research questions, we will only display the stated information and any additional information will be supplemented as proportions of the population in a separate table.

As such our final representations will include nodes for both individual students and the courses they are enrolled in at the same time. Students are color-coded by transfer status (transfer or FTIAC) and eventually indicated in shape by their graduation status, i.e. whether they graduated with a Physics degree, a non-Physics degree, or no degree at all. Edges are not specially represented in any way like through color or line type distinction unless automatically by the program, but it is noteworthy that edges are only drawn between students and their courses, not from any one student to another. This is part of the interactivity of the plot, as once we view a course, we can see all of the students enrolled in that course for the whole academic year.

In summation of the methods and background, we are in the space of new inquiry. While we are not assessing time-to-degree specifically, we do evaluate a portion of graduation-level success in terms of graduation status and graduating with or without a Physics degree, or not at all. As we view courses ‘currently’ enrolled in, the inherent difference between this chapter and its prior sisters emerges– we are in the financial stage of attending MSU and actually taking courses at the four-year institution that, at some point, was the institution intended for graduation. As the space of new inquiry unfolds, we do not abandon the idea of success metrics altogether, but we do recognize the different data pull introduces a roadblock in calculating time-to-degree in higher education similarly to the way we were able to manage in the prior chapters. As such, any dialogue here about financial implications is attached to the courses enrolled in this view, and followed through with recommendations of how to use this tool and process for evaluating the success metrics of graduation with even more consideration and curiosity.

7.7 Results

Outputs from Gephi are exportable as images or files with location and label information for each node and edge type. Within Gephi when a plot is being viewed, one can hover over the individual students, courses, and connections to see information for those pieces at a time. The interactivity of the plots does not export in any manner, and so displayed for this section of results are a series of screenshots portraying the relevant features and findings.

7.7.1 RQ1: Representing Course Connections from IR Databases

The lens of pursuing this analysis in IR methods considers first the sections above about how to access the data and what is housed in the MSUEDW. Part of our exploration considers additionally how these measures are made measurable by IR practitioners. Where in Chapters 5 and 6 we considered time-to-degree in both calendar year and enrollment times, IR practitioners measure time-to-degree in a different manner for transfer students at MSU. While Network Analysis is not employed commonly, we still consider the features that are assessed to IR practices: defining the last institution attended in a manual process as it is not stored as its own column, many of the main SQL pull selection criteria, and other etcetera decisions that shape the data. While we discussed the data construction earlier, the viewpoint of Institutional Research helps shape how we also come to our conclusions about the plot and where our analysis impacts departmental policy.

A large part of our formational effort came through the designing of the SQL pulls and cleaning our data to reflect IR practices. With two total SQL pulls joined together, the effort of reflecting on IR practices showed up in what we were able to pull from the MSUEDW in general. From our pulls seen in Appendix A, we need knowledge of coding schemas that are present and different within each column. For example, the first pull which gathers the course data has three ‘AND’ statements for three different types of depictions of being ‘enrolled’ currently: in the class view *and* term view enrollment statuses, as well as the inner-course specific enrollment status. Other choices in column selection require knowledge of distinction, such as the academic program and academic career being separate columns with completely different categorizations.

Choosing Tableau and Gephi as representative tools also came about through this IR mindset. As data visualization is a highlight of IR practices, Tableau is a strong candidate for visualizations in any form of showcasing institutional data. More pertinent to the results of our efforts, visualizing Network plots was a much more contentious effort in that Tableau does not have any native tools for creating Network plots or performing analysis. The choice of Gephi as an outsourced tool from Tableau is much like deciding where the data is cleaned (Tableau) for where it ends up being displayed (Gephi).

We explored many options for displaying Network plot data back in Tableau *after* utilizing Gephi to create our initial plots. This effort culminated in a demonstration of data curation in Tableau, exporting the curated data into Gephi for formulation of location-based (coordinates) data per node/edge, then re-imported into Tableau for customization based on features of each node/edge. The process requires data cleaning to port only necessary files over to Gephi and then back to Tableau. Namely, to port to Gephi, there must be a separate file for the nodes and edges each: the nodes file requires at least a column for the ‘ID’ of each of the desired nodes, then the ‘Label’ of each desired node, and the edges file must consist of a ‘Source’, ‘Target’, ‘Weight’ (if applicable), and ‘Type’ column. This latter set follows the criteria we introduced earlier about Network Analysis, wherein the ‘Type’ of edge is the distinction of ‘directed’ or ‘undirected’ connections. While the weight can be calculated in Networks that require it, we do not require this calculation in these results. However, if needed, it is recommended to use ‘RStudio’ for this calculation, as there are methods to compute whether a source and target have multiple commonalities requiring a heavier weight to their edge.

Selecting Gephi as the destination of the final plot creation occurred after trial and error with attempting to place back into Tableau and customize from there. However, before jumping ahead to this decision, explaining Gephi and Tableau's other relevant capabilities helps establish decisionmaking of why we settled on Gephi.

Tableau's capabilities relevant to this Network Analysis include and are not limited to: changing node shape, color, or size manually or based on certain attributes of connection, changing edge weight, size, color, or line type manually or based on certain attributes of connection, and adding or excluding certain nodes from view. All of these were tested to form a version of the Network plot, but none of these attempts are present as final plots in this chapter's results.

Gephi's capabilities as relevant to this Network Analysis include and are not limited to: adding, changing, & removing labels for the nodes, editing other node or edge data per desired element, adding or copying columns for extra data, merging duplicate information, defining other node traits such as shape, color, or size either manually or based on certain attributes of connection, changing edge weight, size, color, or line type manually or based on certain attributes of connection, and manual or automatic node placement and relocation. All of these customization forms were performed in Gephi for formation of the final Network plot.

The difference in ease of use was the primary decision driver for choosing Gephi as the platform for our final Network plots. In a practitioner's lens, ease of use of a platform is important for quick and replicable practice when considering performing further or more extensive analysis. In addition to this narrative, the process of re-exporting Gephi data was complex in how the location data, exported as x- and y-coordinates for Tableau to interpret, did not represent connections better than Gephi could in its native program for the purposes of relaying our intended message.

To the actual definition of course connections, we ultimately decided upon representing connections between students and their enrolled courses in order to understand a more practical enrollment view rather than social connotations of being enrolled together with peers. In this view, showing students enrolled in courses in Fall 2017 and Spring 2018 gives a snapshot of an Academic Year's worth of coursetaking among enrolled Junior-level students. This brings us to a part of Gephi's interface that ended up quite crucial to our results formation, which is an interactive element to the plot display.

As one hovers over the generated Network plot in Gephi, the nodes hovered over become isolated on the plot. For example, if one hovers over one of the course-identified nodes, that node would remain its full color while most of the other nodes fade away to let the course node stand out. The course *and* all of its connections (edges) remain visible and stark, and so one can easily identify the course and all of the students who were enrolled in that course for our Academic Year of 2017. While we will view the plots in the next section, this is necessary to establish how we are assessing course connections. As stated before, a Network plot is identified by the nodes and edges, but can be muddy or difficult to interpret depending on how many nodes and connections are being represented at once. Being able to isolate certain courses in view at a time allows for easy extrapolation of how many students are enrolled in it and of what type they are, as well as parsing out what their graduation status is later on.

Lastly, in terms of how to view course connections, we decided to combine some courses in consideration to condense the amount of courses viewed on the resulting plots. This decision was made also in part by the fact that there are two terms of enrollments, and the pulled data from the MSUEDW sorts these courses by a long code depicting the term of the course, type of course, e.g. 'Chemistry' (in a numeric identifier), and the section of the course, e.g. 'Section 2' (also in a numeric identifier). Differentiating courses by term, course code, and course section allows for complete isolation of courses in case a practitioner has motive to look at section-by-section assessments, such as differences in enrollments or GPA achievement. For this analysis, we chose to pare down courses through the following criteria:

- Combining courses into one node if they are of the same exact course subject and code (e.g., multiple instances of MTH234 combine into one instance), removing section-level distinctions

- Combining **certain** courses if they are of the same course subject and the same approximate level (e.g., CSE231 & CSE232 as CSE2XX), especially if the course is not required within the Physics program

- Combining **certain** courses if the level does not matter as a requirement or is not of analytic interest; this is only practiced here in designating MTH3XX, as few students are enrolled in 300- or 400-level Mathematics courses in this assessment.

Again, these decisions significantly pare down the amount of course nodes that would otherwise be present on the Network plot. A clean presentation is important to the interpretation of results for our second research question, but as well cutting nodes reduces the amount of edges that might be otherwise followed by the eye. In all, the courses present in the analysis going forward consist of 9 Physics courses, 6 Math courses, 11 Engineering-aligned courses, and 1 computation course that was made required to graduate with a Physics degree very recently to this Academic Year assessment of 2017.

The last portion of representing course connections came from thinking on what the format of the plot would depict about the proximity of connections. While we have some focus later on the centrality of certain nodes, or how many connections each course might have with students, we do not deliberately form the plot in order to give *numeric context or measure* to closeness or shortest paths between nodes. Some ways of *automatically* changing the position of the nodes (and therefore the length of the edges) are provided in the native Gephi platform, including titled formations, such as 'Yifan Hu', 'Fruchterman-Reingold', 'Force Atlas', etc [142–144]. These are distinctive formations that, again, automatically change where the nodes appear according to their respective principles of location and connection relationships.

We first condense the nodes using 'Contraction' several times so that the nodes are somewhat ushered toward a random arrangement. 'Contraction' is not an algorithm, but rather just a means of pushing the nodes closer together. Then, we select the 'Fruchterman-Reingold' algorithm for putting the nodes in a more appealing looking circular formation. Then, we can continue to contract, or select the 'Noverlap' arrangement selection that forces the nodes to not be overlapped with each other. Then, we can decide whether manual arrangement might be desired, as nodes can be dragged around and placed elsewhere. We moved a few of the more central courses to be more literally in the center of all of its connections, for example CSE2XX and MTH234 were both manually moved to be more in the center of the overall arrangement. We also manually pulled students who ended up having no relevant course connections out to the bottom right, as there was emptier space there from moving other courses.

While closeness is not being numerically measured, it was overall slightly considered in this final plot curation, and therefore we will comment on proximity of some courses to some student types visually. The remainder of assessment of results lies in the centrality of courses.

7.7.2 RQ2: Investigating Course Enrollments of a Junior-Level Physics Cohort

The culmination of Network Analysis through Gephi resulted in connections between 61 students and the 27 courses pared down to be enrolled in for the Fall 2017 and Spring 2018. From here on out, this will be referred to as AY2017 (Academic Year 2017). As a reminder, students are typically enrolled in more than course and can seem to be enrolled in more courses than typical for a single semester, as these plots represent the courses enrolled and relevant to the analysis for two semesters of attendance.

Figure 7.2 represents the first plot generated by the Gephi program after cleaning and relabeling the course nodes to be more general and relevant. This plot contains several features which were also customized within Gephi's interface. Student nodes are represented as dark red for transfer students and black for FTIAC students. The courses are colored by their alignment with certain programs. Physics courses are blue and not re-coded at all for the sake of retaining potential interesting dialogue in lower-level versus higher-level courses. Math courses are colored green and re-coded only in the concatenation of 300- and 400-level Math courses as MTH3XX as there are two 300 *at least* level courses, and so 400-level courses can also satisfy this requirement. Engineering courses are colored orange and, as established in our prior criteria in RQ1, were partially re-coded depending on the amount of sections or levels of courses available and enrolled in for AY2017. The last course is a special coding course under the Computational Mathematics, Science, and Engineering department, which was established a few years prior to AY2017 and around this time introduced CMSE201 as required for graduation with a Physics degree. This course is concatenated with an instance of CMSE202 to make CMSE2XX and is colored vibrant pink.

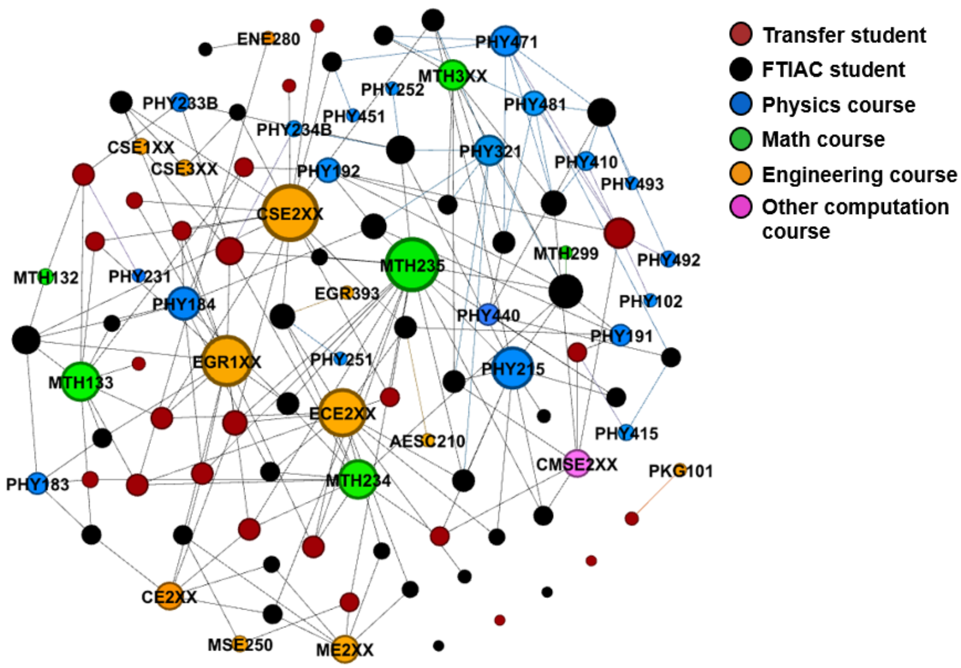


Figure 7.2 Generated Network plot depicting the courses enrolled by Physics Juniors in the Academic Year of 2017. Courses are color-coded by subject relevance, including Engineering, Physics, Mathematics, and a special computation course. Transfer and FTIAC students are distinguished as dark red and black respectively.

As our first shown representation, there are many interesting things to both point out and remind from prior established information about this Network Analysis process. To remind, the placement of the nodes was decided by a combination of automatic and manual arranging. The first place our eyes as the researchers wants to go is where the transfer students are enrolled, and perhaps where they may be congregating on the plot. To support answering this question, we notice that orange nodes, or Engineering courses, ended up primarily on the left or bottom-left of the plot. As well, a majority of the Physics courses end up somewhere to the right or top-right of the plot. Math courses are relatively scattered around the plot, with the MTH3XX node a bit closer to the array of Physics nodes and the MTH132 and MTH133 courses a bit closer to the Engineering nodes. These respective Math courses were not manually moved after employing the Fruchterman-Reingold algorithm. Lastly, the CMSE2XX course node sits to the bottom right of the plot, above where the manually-placed students with no relevant course connections sit.

Before assessing the next plot with graduation-level information per student, we want to note

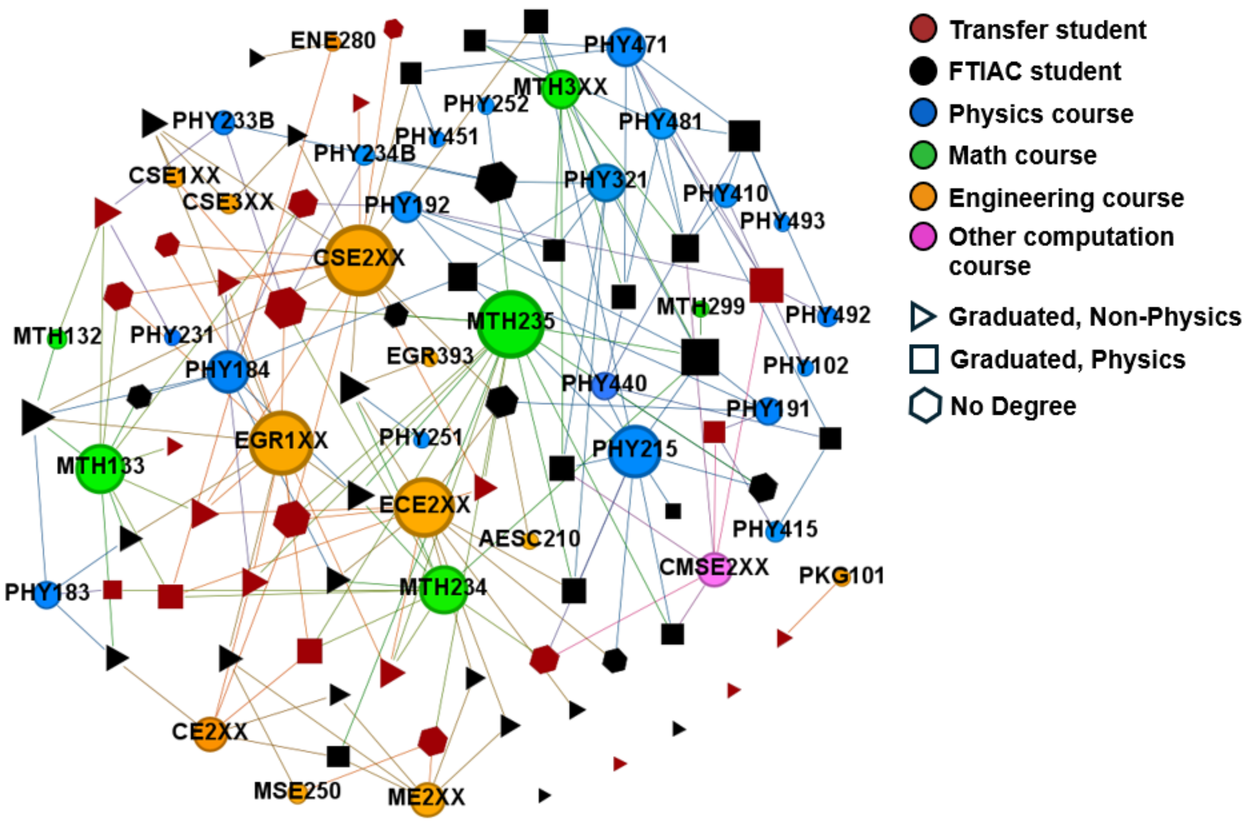


Figure 7.3 Generated Network plot which shows the specific graduation status of each student enrolled along with the courses they are enrolled in per Academic Year 2017 as Physics Juniors. Students who graduated with Physics are depicted as squares and those who graduated in a non-Physics major are depicted as triangles. Those who did not graduate are depicted as hexagons. The color distinctions between courses and students remain the same as prior.

that the graduation-level plot having shapes for the student nodes is displayed on a portion of the Gephi interfact in which one cannot hover over the nodes and see their individual connections as described earlier. Therefore, there will only be one plot displayed with graduation-level node information.

Figure 7.3 contains the graduation-level plot, which depicts the same color-coding as Figure 7.2 for both students and courses and keeps all nodes in the same array as they were. Gephi automatically recolors edges to match the course which the connection comes from, however edges still do not have a 'direction' to consider, and so this is merely an aesthetic difference. Here, we see more nuance in our student nodes and wonder then about certain shapes and locations relative to the course nodes we viewed through a similar method before. Triangular student nodes are those who graduated, but without a Physics degree. Those with a square node are those who graduated *with* a Physics degree. Those who are hexagonal are students who have no degree information, and therefore likely did not graduate from MSU with any degree. We saw the spread of these students counted in Table 7.1 by graduation status and noticed that of the 24 transfer students in the model, 11 graduated without a Physics degree and 5 graduated with a Physics degree, leaving 8 without any MSU degree. Within FTIAC students, of 37 total, 16 graduated without a Physics degree, 15 with a Physics degree, and 6 without any degree.

With that refresher in mind, we notice again proximity-wise that students who graduated without a Physics degree tend to the left or bottom-left of the plot, where those who graduated with a Physics degree are more commonly at the right or top-right. Students without a degree are more scattered, but the transfer students in this collection are a bit more on the left side of the plot.

We are not assessing closeness or proximity as a quantitative measure, especially considering our few manual adjustments, and so after visual inference we move on to our assessment of centrality to show more about specific courses and their enrolled students for AY2017. The means of assessing this was mostly a manual process, as there are few enough courses left to count the connections to each of them one by one. This counting will be divided up by each student type and their graduation statuses, but first we showcase examples of how this manual process was done.

Figure 7.4 represents one of the most central Physics courses for an example of how the interface looks when isolating a node and its connections. As stated before, the node isolated, its edges, and all of the student nodes connected to it become stark and easily noticed, where the remainder nodes and edges fade. As well as this, we are unable to perform this interactive feature on the plot with graduation-level data, and so the remaining plots will have only circular nodes on them as per the first generated plot.

As we note in Figure 7.4, Physics 215 is 'Modern Physics', which comprises of multiple subtopics of Physics such as thermodynamics, relativity, nuclear physics, and other subtopics. It is a course that is recommended from Figure 7.1 by the department to be taken Sophomore year in the Fall term of that year in order to take Physics 321, or Classical Mechanics in Spring of

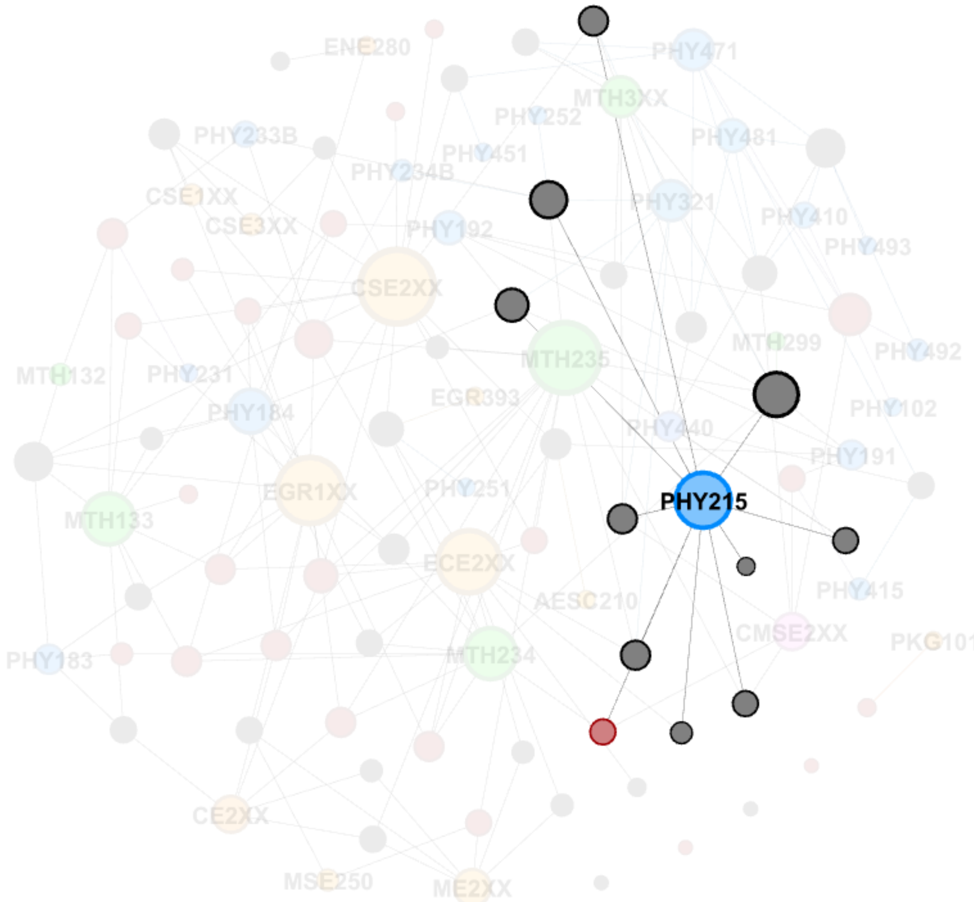


Figure 7.4 Network plot depicting Physics 215 (Modern Physics, 'Sophomore-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 1 transfer student and 10 FTIAC students are enrolled in 2017 for a total of 11 students.

Sophomore year. As one of the most central courses of the Physics courses listed, we mark that 1 transfer student and 10 FTIAC students are enrolled in this course over AY2017, meaning that 11 total students are enrolled in this course as *Juniors*.

In lieu of assessing every specific centrality with a supplementary plot, the remainder of the Physics courses that are required for a Physics degree are isolated and shown in plots in Appendix C. Instead, we show a table below with the count of required Physics courses' enrollees and their respective graduation statuses in Tables 7.2 and 7.3. For the sake of brevity, only Physics courses required to graduate are in this table.

As we view this table, we consider that these are only required courses, leaving off PHY102,

Course	Student Type	Total N	N No Grad.	N Grad., No Physics	N Grad., Physics
PHY183	Transfer	1	0	0	1
	FTIAC	3	0	3	0
PHY184	Transfer	3	1	2	0
	FTIAC	5	1	3	1
PHY191	Transfer	1	0	0	1
	FTIAC	3	1	0	2
PHY192	Transfer	2	1	0	1
	FTIAC	3	0	0	3
PHY215	Transfer	1	1	0	0
	FTIAC	10	3	0	7
PHY321	Transfer	0	0	0	0
	FTIAC	7	1	0	6

Table 7.2 Each course separated by its FTIAC and Transfer student enrollee count for the entire Academic Year of 2017 (Fall 2017, Spring 2018). In this table are all Physics courses recommended to take at Sophomore-or-Below level, but that students are enrolled in as Juniors for 2017. For the sake of brevity, only Physics courses that are requirements for graduation are assessed. Included are PHY183 and 184, Introductory Calculus-Based Physics in Kinematics and Electricity and Magnetism; PHY191 and 192, Introductory Laboratory courses; PHY215, Modern Physics; and PHY321, Classical Mechanics.

PHY231, PHY233B, PHY234B, and PHY252. These courses left off are not required to graduate per se, but in certain combinations can fulfill requirements for PHY183/PHY184, for example. There were a few transfer students enrolled in these courses, but overall they did not have many enrollments across the students considered. An additional reminder is that most students are enrolled in more than one course in this model, so these are not unique enrollments from each other most of the time.

Otherwise, Table 7.2 shows the courses required for the Physics degree that are recommended to be taken at the Freshman or Sophomore level of attendance through Figure 7.1. These courses are enrolled in fairly sparsely aside from PHY215 and PHY321, which are mostly populated by FTIAC students (10 and 7 FTIAC students respectively). The course with the most transfer student enrollments for this group is PHY184, or introductory calculus-based Electricity & Magnetism with 3 transfer students enrolled. The spread of graduation statuses among these courses, again recognizing there can be overlapped students among them, mostly shows that enrollments in the Freshman-level courses (PHY183 and PHY184) are populated in a spread across the three degree statuses, especially graduating but without a Physics degree. The Sophomore-level courses (PHY215 and PHY321) are strongly populated by FTIAC students, most of which graduated with Physics degrees. Still, PHY215 specifically has 4 instances of students enrolled who did not earn any degree from MSU. PHY191/192 are both lab courses and are each one credit, which makes taking them rather flexible in timing for most students.

We view the Junior-and-Above Physics course enrollments in Table 7.3. Separating these tables helps to understand where lines may be drawn between upper and lower level courses. This is our first glance at enrollments for courses that *should be* taken at Junior-level as we assess currently enrolled Juniors for AY2017. Across the board, PHY471 or Quantum Mechanics I is the most populated with 7 enrollments, 1 transfer and 6 FTIAC students. *All* of these students graduated with Physics degrees. Similarly, a majority of those enrolled in these Junior-and-Above courses graduate with Physics degrees, aside from *one* FTIAC enrollment in PHY440 (Electronics Lab) that did not graduate.

To note from Appendix C, as we hover over most of these Physics courses, a majority of the enrolled students are located are near them; PHY183 and PHY184 are the only Physics courses located on the left of the plot(s), which many of the students on that part of the plot are enrolled in Engineering courses. As we hover over these Engineering courses, many of the students enrolled in them are on the left side of the plot. With that, we represent the next sequence of courses as the Engineering-aligned Table 7.4.

This represents the Engineering courses that were condensed after assessment of how many sections and types were enrolled in, resulting in a pared-down combining of many courses. No Engineering course is required for a Physics degree, and so it is reasonable to say that Junior-level Physics majors should perhaps be enrolled in Physics courses at this time instead of Engineering-aligned courses. Our centrality counts show that *many* students are enrolled in these popular Engineering courses. The most central course is CSE2XX, which comprises of a few different

Course	Student Type	Total N	N No Grad.	N Grad., No Physics	N Grad., Physics
PHY410*	Transfer	1	0	0	1
	FTIAC	2	0	0	2
PHY415*	Transfer	1	0	0	1
	FTIAC	1	0	0	1
PHY440*	Transfer	0	0	0	0
	FTIAC	4	1	0	3
PHY451	Transfer	0	0	0	0
	FTIAC	1	0	0	1
PHY471*	Transfer	1	0	0	1
	FTIAC	6	0	0	6
PHY481	Transfer	1	1	0	1
	FTIAC	4	0	0	4
PHY492	Transfer	1	0	0	1
	FTIAC	1	0	0	1
PHY493	Transfer	0	0	0	0
	FTIAC	1	0	0	1

Table 7.3 Each course separated by its FTIAC and Transfer student enrollee count for the entire Academic Year of 2017 (Fall 2017, Spring 2018). In this table are all Physics courses recommended to take at Junior-or-Above level, but that students are enrolled in as Juniors for 2017. For the sake of brevity, Physics courses required for graduation are assessed, and courses recommended to be taken at Junior-level specifically are marked with asterisks. Included are PHY410, Statistical Mechanics; PHY415, Methods of Theoretical Physics (replaceable with any 300+ level math course); PHY440, Electronics Lab; PHY451, Advanced Lab; PHY471, Quantum Mechanics I; PHY481, Electricity & Magnetism I; PHY491 and 493, High Level Physics Capstone Courses.

Computer Science Engineering 200-level courses. 16 students are enrolled in the array of CSE2XX courses, evenly split up into transfer and FTIAC students with 8 each. Only 2 FTIACs in this grouping graduated with a Physics degree, where the remainder are spread among attaining no degree or attaining a Non-Physics degree.

The other popular Engineering courses were EGR1XX, mostly sections of Engineering 100 which is Introduction to Engineering Design and is required for College of Engineering majors, then ECE2XX which is an array of Electrical Engineering courses. These had 13 and 14 enrollments respectively, similarly spread across either attaining a Non-Physics degree or no degree, and very few Physics degree earners considering potentially overlapping student enrollments. Most of these

Course	Student Type	Total N	N No Grad.	N Grad., No Physics	N Grad., Physics
CE2XX	Transfer	3	1	1	1
	FTIAC	3	0	2	1
CSE2XX	Transfer	8	4	4	0
	FTIAC	8	2	4	2
ECE2XX	Transfer	5	1	3	1
	FTIAC	8	2	5	1
EGR1XX	Transfer	9	4	4	1
	FTIAC	5	0	5	0

Table 7.4 Each course separated by its FTIAC and Transfer student enrollee count for the entire Academic Year of 2017 (Fall 2017, Spring 2018). In this table are Engineering-aligned courses that have more than two enrollments for the sake of brevity. Courses may be condensed to blanket over many similar-level courses, but none of these are required for the Physics degree. Included are CE2XX, Civil Engineering; CSE2XX, Computer Science Engineering; ECE2XX, Electrical and Computer Engineering; and EGR1XX, General Engineering.

students are, as seen in Appendix C, located on the left side of the plot near the Engineering courses.

Our final table represents the remaining courses, all of which are rather important to the Physics degree but did not have remarkable locations on the plot(s). Noting Appendix C for visual reference of some of these courses, Table 7.5 shows the Math, CMSE, and residual students without relevant course enrollments. Here, we see that Math is, indeed, extremely popular to be signed up in, and therefore we see high centrality for the instances of MTH133 (Calculus II), MTH234 (Calculus III), MTH235 (Calculus IV or Differential Equations), and the MTH3XX call which includes 300- or 400-level enrollments. Many transfer students are enrolled in the Math courses below 300-level, mostly in Calculus II, III, and IV. To remind, these courses are required to graduate, and therefore show up in Figure 7.1 as recommended to be taken in Freshman and Sophomore year. As well, these courses are pre- or co-requisites for most of the Physics courses, especially 400-level Physics courses. Notably, the array of degree earners is spread out across degree types, not particularly leaning one way or another, *aside from* MTH3XX which contains 7 FTIAC enrollees, of which *all* 7 graduated with a Physics degree. It is, however, interesting that as the Math course increases in code to a higher Calculus, there are slightly more Physics degree earners, e.g. 4 Physics degree earners

Course	Student Type	Total N	N No Grad.	N Grad., No Physics	N Grad., Physics
CMSE2XX*	Transfer	3	1	0	2
	FTIAC	3	0	0	3
MTH132*	Transfer	1	0	1	0
	FTIAC	1	0	1	0
MTH133*	Transfer	6	2	3	1
	FTIAC	4	1	3	0
MTH234*	Transfer	6	2	1	3
	FTIAC	4	0	3	1
MTH235*	Transfer	7	3	3	1
	FTIAC	8	3	1	4
MTH3XX*	Transfer	0	0	0	0
(+ MTH4XX)	FTIAC	7	0	0	7
No Relevant	Transfer	2	0	2	0
Courses	FTIAC	2	0	2	0

Table 7.5 Each course separated by its FTIAC and Transfer student enrollee count for the entire Academic Year of 2017 (Fall 2017, Spring 2018). In this table are a unique computational course required for the Physics degree, several levels of mathematics courses, and the etcetera information for students who had no connections to be thorough. Courses required to graduate with a Physics degree are noted with asterisks. Included are CMSE2XX, Introduction to Computational Modeling in Computational Mathematics, Science, and Engineering; MTH132 and 133, Calculus I and II respectively; MTH234 and 235, Calculus III and Differential Equations respectively; and MTH3XX, including a broad range of 300- and 400-level courses, of which Physics majors need two courses passed to graduate.

among the 10 enrolled in Calculus III and 5 among the 15 enrolled in Calculus IV. Additionally interesting, of the 10 Junior-level students enrolled in Calculus II, 6 of them earned Non-Physics degrees, and Calculus II is considered a Freshman-level course by the department as mentioned above.

The CMSE courses were an interesting addition, as their enrollment tally is lesser than Math, but most of the 6 total enrollments graduated with Physics degrees. This course is required for the Physics degree, as made required close in time to this AY2017 assessment.

Lastly, the students with no relevant enrollments were 2 transfer students and 2 FTIAC students, with all four of these students earning Non-Physics degrees. Barring other details that were pared down within Gephi before plot creation, it is safe to presume that with no Engineering-related enrollments, they may not have earned Engineering degrees either. There are also several students who are only enrolled in one or two 'relevant' or 'interesting' courses that we pared down to, which calls for further investigation of what they are actually graduating with or where they wish to be if not in Physics as a Junior.

7.8 Discussion

This work is full of new inquiry that has not been explored in the prior chapters. As a chapter that does not focus on time-to-degree, we turn to the success metric of graduation status and graduating *with* or *without* a Physics degree to drive the narrative of data-driven policy. What policies do we see arising here? As we described in our introduction and background, this is a much more intimate look through a department's enrollment instances, where our views from Chapters 5 and 6 were much broader and, certainly, more 'Institutional' in framing. Showing a snapshot of Juniors had been inspired by the findings of Chapters 5 and 6, knowing that Juniors have particularly interesting dynamics in transfer student experiences; that is, if one *comes in* as a Junior, they are most likely to be subjected to the 60 credit transfer limit as long as they are a two-year college transfer student, which most in this chapter are as well.

Moving away from representing time-to-degree is a conversation about what this department, then, might care about. Institutional Research often speaks to the institution's experiences, curiosities, and policies, but this finer comb into one department becomes more local politicking about *retaining* students rather than seeing how *quickly* they might graduate. Time-to-degree represents for this dissertation the culmination of time spent in higher education, where the department assessing its current enrollment statistics might view that as a metric that takes a backseat to whether or not they actually *have* graduating Physics students.

As we partner this with our results, we see that many Physics Juniors are in fact enrolled in Engineering courses instead, especially transfer students who, as stated prior, are not particularly transferring *in* as Juniors, but have made it to *or* transferred in at Junior status in AY2017. Again, most of these transfer students transferred from a two-year college, so our dialogue from Chapters

5 and 6 through this lens can solidly continue; our results show that these Junior-level Physics transfer students largely do not graduate with a Physics degree or do not graduate with a degree from MSU. Their enrollment patterns reflect this, as seen in being enrolled in a multitude of Engineering-aligned courses when they are actually Juniors in Physics. However, of the transfer students that did earn a Physics degree, most of these 5 students were enrolled in some type of 400-level Physics courses or *primarily* courses required for the Physics degree, with the exception of one Physics degree earning transfer student who was enrolled in two Engineering courses and Calculus III during AY2017.

It shows through many of these patterns we pointed out that Physics students are very commonly seeking out some type of Engineering course, even at Junior Physics status. Most transfer students were enrolled in at least one Engineering-aligned course, and oppositely, many FTIAC Juniors were rooted fairly strongly in *required* Physics courses, but perhaps not particularly *Junior-level* courses. This is also an interesting finding– even among all of these Junior-level students, there are a large amount that are primarily enrolled in Sophomore-level or below Physics courses or non-Physics-required courses.

The Network Analysis suited the pursuit of knowledge through an IR lens in both seeking a desirable format for representing course connections and enrollments, but as well seeking a format that may be interesting and desirable for a department's perspective on its success metrics. Gephi suited this plot curation for our decisionmaking around what tool best suited IR practices, as well as what was able to connect to IR databases and form data curation for formulating what the course connections even ended up as.

While we do not focus on time-to-degree, we see financial implications arising in a more local format of graduation success: at Junior-level status, a student may be expected to be rather solidified in their pathway through attaining *that* degree they are enrolled with as a Junior. By then, the student has acquired *at least* 56 credits, either as a FTIAC through mostly MSU credits, or as a transfer student through mostly credits transferred from other institutions. By the time Junior status begins, these students should be almost halfway done with their degree, that being a Physics degree. We see that many of these students do not earn a Physics degree at all, especially transfer students. This brings about many interesting implications about departmental dynamics around advising practices, mitigating or encouraging interest with the Engineering programs in particular, or other means of assessing and advising what the student should ideally be enrolled in to earn the Physics degree.

Local perspectives on policy allow for more flexibility around what sprouts from inquiry like this work. These representations showcase interesting data that can address potential spots or gaps in articulation of transfer credits in the Physics program, intervention at or before transfer to acknowledge true degree attainment intention, and to view whether Junior students are in general enrolled where they 'should' be enrolled in Physics courses. While we see many students enrolled in Physics courses, they are not as commonly enrolled in Junior-level Physics courses as they are in Sophomore-or-below courses. In relation to our framework, the flow of data-driven policy may not always begin and end at the same policy through only one success metric analysis. The Network Analysis presented in this chapter supports the idea that transfer students need support from their transferring departments and institutions to enroll in and grow into the majors they want to succeed in, and perhaps not to be Juniors in a major they may transfer out of and not graduate from altogether.

7.9 Limitations

Network Analysis bears a lot of interesting limitations around visual interpretation alongside more traditional quantitative reasoning. Constructing the visual is particularly limited by the program or tool being used for visualization, exemplified in our very choices of Tableau and Gephi. Tableau does not have any native programming suited for Network Analysis, defining node or edge locations, or interacting with customization beyond color, size, or shape of nodes/edges. Gephi can do each of these well, but is limited then by other Network Analysis features such as the choice between freely moving nodes/edges or needing their proximities fixed for certain numeric analysis such as nearness.

As a continuation of our prior chapters, in this new data pull, we did not perform any outlier removal (wherein our prior removal was related to time-to-degree metric outliers), and were limited by interesting factors of transfer experience prior analyzed such as In-State attending, prior institution type, and other facets that could not all be reasonably explored on one visual representation. Some graduating students identified among those represented graduated with multiple degrees, but were condensed to whether or not one of them was a Physics degree, which limits the ability to speak on those who may have double majored in this pathway.

While we were able to draw in interesting demographics or other levels of assessment of these students' traits, Network Analysis is a very difficult tool to represent so many features and traits at once. Pulling for these traits was a feat, but we did not pursue further analysis with most of them aside from establishing some extraneous information about the transfer students.

Other methodological limitations came about in specific Network Analysis practices, such as referring to closeness of nodes while choosing to manually move some nodes. While there are algorithms within Gephi best suited for assessing certain measures of Network Analysis, we did not stick to principles of one algorithm or another and instead settled on a mixture of automatic and manual manipulation of nodes in order to show an interpretable and interesting generated Network for broader analysis. Centrality was also performed manually as a quantitative measure, while there are likely better programs for automated calculations of this measure.

7.10 Conclusions & Broader Implications

We first look to financial implications of this work. Alluded to before, this is a more local view of course enrollments rather than our perspectives of credit loss or time spent in higher education towards financial argumentation. When we look more closely at enrollments at the destination institution (MSU), we are able to see and count the number of courses enrolled in, which all have credit assignments to them, meaning at a per-credit cost for 2017, we can approximate how many credits of relevant coursework these students were taking as Juniors. It was established before that Junior & Senior students at MSU pay higher tuition rates than Freshman and Sophomore students. This, along with our prior sentiments about this snapshot being of Junior-level students in Physics and seeing less than half of *both* FTIAC and transfer students graduating with Physics degrees, puts forward implications about what Physics majors are paying for at Junior status: to attend Engineering courses or perhaps lower-level Physics courses than Junior-level.

It is to say that Junior status does not always mean the number of calendar years spent in higher education, and is merely a status attributed to the amount of credits held by the student. When we attribute this status to credits, we directly link it to an estimation of that per-credit tuition cost, and come to understand what about 'time' might still be relevant despite not being measured. Being enrolled in lower level courses or non-Physics-required courses pushes students into holding higher amounts of completed credits and therefore *into* being Junior or Senior status and paying higher tuition to be less far along in the pathway to graduation. A Physics department, as well as any other individual major department, cares greatly about the retaining of students to earning their degrees. They may not particularly bargain with time-to-degree as a measure worth pursuing analysis, especially if the student decides to ultimately change majors anyway.

What is to be done is left to the implications of our framework. Flowing through many policies both written and unwritten, assessing graduation success metrics, and leading us to this chapter of work where we inquire what more there is to be seen on a much closer look, shows a flow back in to assessing policy. However, the flow of data-driven policy is never quite that linear. We learn about broad institutional policy from what works locally in smaller departmental changes or the work of the colleges rather than the whole institution. We learn about smaller departmental policy from the exploration and curiosities of Institutional Research and find interesting and closer measurements to local dynamics, particular subsets of students, and places that are more receptive to change. It is easier to talk to a department about articulation agreements within their program and local colleges' reciprocal programs, though it still requires people with knowledge about how to implement these practices. In all, the institution learns from its localized constituents, and the local politics and policies grow from reassessing what broader institutional barriers may inspire a keen eye on what is happening to the students around us.

Higher education is expensive. Choosing the right major is sometimes a hassle. Knowing where you should be exactly by a certain student level and *actually getting there* sometimes needs a helping hand, resource sharing, and careful advising. The less that students lose out on financial commitment to higher education, the more they can invest into their desired pathway and, in all, address graduation success in a more timely, optimized, and stress-free manner.

CHAPTER 8

OVERALL CONCLUSIONS & FORWARD

Policy in the realm of higher education impacts beyond a singular institution's decisionmaking. It decides what the practitioner must do to assess what's going on around them. It decides what the student must do to navigate them, to make it to a finish line for which the success around finishing is defined by the path it took to get there. Much of the effort of this dissertation shaped facing policy through a data-driven mindset and set of practices through the framework, which comes to understand a policy through how we observe students moving through that policy and where questions arise because of that phenomenon. Utilizing MSU's cases of a broad, explicit policy (the 60 credit transfer limit on transfer from two-year colleges) and local, less explicit policy (departmental requirements to earn a degree) allow us to show students' navigation around them. What *does* hitting the transfer limit do to students? It certainly does not serve them or support them. What *does* navigating high-level curriculum look like after transfer? Junior-level course enrollments shape an intriguing picture of graduation trends for those enrolled in Physics at such a key time period of higher education. Much of our work focused toward Junior status analytics, as those who were key to interacting with these particular policy lenses, but the beginning of this work strived merely to understand TYC transfer student perspectives in the way we measure *anything* about them. Using time-to-degree as a footstool, we are able to challenge the very foundation of how such a metric is measured and whether TYC transfer student experiences can be aligned with the decision of which measurement type to settle on: the traditional (calendar time) or the literature-based (enrollment time).

Our findings show that enrollment time-to-degree is different from calendar time-to-degree in many ways, showing how the numeric difference between the times on average across the students can be compared between groups, and that for all TYC transfer students no matter the level of credit they bring in, the difference in metrics is significantly different from First-Time-In-Any-College (FTIAC) students' time-to-degree differences. Notably, though, as incoming credit amount increases, or rather as academic level status on arrival to MSU increases up to Junior level, the difference in the differences gets much higher, and much more significantly different from FTIAC time-to-degrees. The case of Junior students expands in interest immediately, with noticing that their time-to-degree metrics, regardless if individual or calculated as the difference between the two, have large effect sizes between FTIAC students all around and small-to-medium effect sizes between the other transfer student groups. In all, enrollment time-to-degree stood as significantly different and an ever-widening gap from calendar time, the traditional measurement, and brought to light many experiences of TYC transfer students: that time-to-degree changes per student group regardless of the metric type, and that we see a strong indication that adjusted credit and transferable credit levels strongly reactive in a model with all TYC transfer students, despite Junior-level transfer students being those who are primarily experiencing adjusted credit.

As it is, adjusted credit is a difficult 'metric' to define, in viewing how an institution chooses to deal with it, the level of which the adjustment might occur due to a chosen limit of incoming credits, and in how a student reacts to which and how many credits might be adjusted off. In MSU's case, the limit of 60 credits again applies only to TYC transfer students, meaning the other 60 will be earned at MSU for a 120 credit degree to be conferred (with the exception of most Engineering degrees). With understanding that incoming Junior-level students are the group that are able to reach this credit amount, they are by far the primary subset of TYC transfer students that experiences adjusted credit and at a much higher amount, seeing almost a full term of credits adjusted off on average. While time-to-degree is a bit more difficult to place financial estimations upon, enrollment time-to-degree helps narrow in the perspective of per-credit cost of tuition, which aligning with this finding of adjusted credit on entry aids the projection of just how much money and time might be lost from interacting with this policy.

The additional perspective of another graduation-level success metric gives a more equivalent comparison to what happens with credit on entry to MSU. Excess credit acts as a foil and a juxtaposition to credit loss on entry, as the excess credit is calculated on graduation as the difference from how many credits are required to graduate and how many are actually held, and that time has passed between entry and graduation in order to navigate and negotiate the credits earned at MSU to achieve graduation. Additionally, defining another aspect to credit loss, wherein the numeric adjusted credit is joined by a more identity-based allocation of incoming credits as 'general university credits' brings several potential interactions into play. These findings of two levels of credit loss with two levels of graduation success metrics was explored by breaking transfer students up into academic level, then by each respective credit loss population: either above or below half of their credits becoming GCUs (lost identity of credit), then either with or without any amount of adjusted credit on entry (numeric credit loss).

For all TYC transfer students, excess credit on graduation and time-to-degree do not seem to be strongly impacted by GCU credit level differences, until disaggregated by academic level, for which then Freshman & Junior and Sophomore & Junior comparisons for those with more than half of their credits being GCUs become significantly different, to a higher effect. This is important with the recognition that entering Junior transfer students having half of their credits becoming GCUs is a much higher amount of credit in general. As well, comparing these populations for those with and without adjusted credit must also recognize Juniors for experiencing adjusted credit at higher rates due to the credit limit. Therefore, the base comparison of all TYC transfer students with or without adjusted credit having a significant difference in time-to-degree to large effect is extremely hard-hitting. While excess credit does not show a similar effect size, its t-test for significance still yields a significant difference in the populations' excess credit amounts.

Experiencing credit loss certainly shows up differently in Junior-level transfer students, and especially culminating differently in these perspectives of success. Narrowing in on Physics students aimed to tighten this case to a more specific window of post-transfer dynamics, narrowed in to those who entered as Physics majors for our first data pull. With statistical comparisons having less power at small N, we rely much more on findings from the general statistics of the *types* of courses brought in by these students. They are bringing in a lot of math credits, with more than a third of those math credits becoming GCU credit. Physics credit come in at around 6% of their held credit, though with very little GCU credit held that is Physics-based. Overall, these students experience quite a high amount of excess credit on graduation and an average enrollment time-to-degree of just above four years, *and* most of these students graduate with engineering degrees instead of Physics degrees. With many of these Physics students transferring in as Sophomores or Juniors and seeing an average of almost 16 excess credits on graduation — most of them also graduating with Engineering degrees — it warrants even deeper exploration into what attendance at MSU is like after enrollment.

With a different data pull perspective, we round out our findings through students enrolled in 2017 who are Juniors in the Physics major at MSU. This window is necessary for painting a critical time period where students are in the prime around-the-corner bend of credits to conferring a degree. They are attaining the latter half of their degree credit, and should theoretically be enrolled in courses that align with their degree major. We consider both transfer and FTIAC enrollees, as well as noticing for transfer students that they may enter at a certain academic level other than Junior-level, but in our representation are Juniors at the year of 2017. Using Network Analysis allows us to craft inquiry that goes beyond strictly numeric analysis, using this technique to represent the courses at MSU these students are enrolled in with students and courses as nodes and enrollment of students in courses as edges. Recognizing local policy in the course requirements in Physics for graduation, and the more grey-area policy of a recommended course pathway by the sponsoring department providing implications of which courses are 'Junior-level' or not, we get a much higher degree of nuance for what Physics courses these students *should* be enrolled in, and what they actually *are* enrolled in. Our findings suggest that there is a high proportion of transfer students taking non-Physics-required courses, and these students are typically graduating with a non-Physics degree. There are also a high amount of FTIAC students enrolled in non-Physics-required courses and graduating with non-Physics degrees. Of those enrolled in Physics courses reflective of Junior status, many of these students in both distinctions graduate with Physics degrees. This perspective of course relevance to degree, what it means to be at Junior status, and what the department expects from Junior status, paint a very interesting picture of the realities of department-level politics and bring important implications to local policies we can consider to aid this phenomenon.

Overall, the transfer policy outlook suggests that interaction with known transfer policies speaks strongly to success metrics, and vice versa. Transfer students each show interesting dynamics with time-to-degree differently from FTIAC students, allowing us to make a firm suggestion to utilize the enrollment-based time-to-degree calculation for its consideration of financial dedication to higher education. As well, transfer students do experience credit loss and the definition of that loss can vary, but it is worth exploring deeper what broad and local implications of losing credit may mean, whether institutionally seeing how students experience numeric credit loss, or locally seeing what credits are and are not specifically transferring where students need them to be. With a tool able to view course enrollment, we inspire and encourage local change and reform for aiding students in their desired pathways and recognizing where they want to be. Success is not always graduating with the degree *we* want them to have, nor in an 'on-time' fashion. Success shapes from different roots for transfer students, but is shaped nonetheless, and we have the ability to aid that shape, not make unnecessary cuts to their form. Financially, our students suffer when our policies do not serve them, as evidenced by our success metric implications and visual references to enrollments in Junior year. All of these findings additionally highlight the care we should take as practitioners and researchers in intentionally supporting their pathways with results from our work.

8.1 Toward PER, IR, and Administration

Each and every space I have observed and lived in for my pathway through higher education speaks to this work, and my work to them. I have spoken at length about the intersections and differences between Education Research and Institutional Research, whether as how practitioners or researchers perform their work and shape results differently or in the shaping of intentional and supportive research for the betterment of those being researched upon. Additionally, as this dissertation lives in the folds of policy and data, it is additionally and personally important to speak to the administrations to which this work may speak in all of its abrasive or supportive language and findings. In all of these spaces, I will speak in regard to upholding transfer student experiences.

8.1.1 Toward Physics Education Research

Physics Education Research thrives on the principles of supporting student voices [2]. Quantitative methodology, both in and out of the Physics-specific discipline of Education Research, is rightfully and often challenged for the inherent reshaping of *people* into *points of data*. Mathematization is not solely a phenomenon of Physics curriculum for which we routinely keep in check and balance. It is also a phenomenon of our methodology, such that if we focus too much on getting the analysis to work, we lose sight of who we are working with and the sensitivities that come with paring down too much humanity. When we are careful, there is a beauty in choosing our numbers and choosing our people. Shaping our population has the ability to project out an image looking roughly like the individual if we take care in finding and retaining critical experiences.

The work performed here began strictly in PER and was not, in my first experiences with it, intentional work. It took ages to learn that we were not very well or correctly defining transfer students at all. In a data-driven framework, we strive to select best practices for the sake of challenging our theme, here being policy. No matter the theme or subjects studied, one of the most important parts of learning intentionality was speaking to those who understand the subjects, the theme. My intersection with Institutional Research challenged my perception of how I understood the impact of my Education Research. Who do I support with my work, and why do I choose to do it? The philosophy of data-driven work is that the whole point of the data is being intentional every step of the way to change and tweaking understanding where it is not shaping up. Eventually, I spoke to the right people and learned how to define a transfer student properly. Then, I turned back and asked them to tell me exactly where they do and do not support said transfer students.

Policy and transfer work are highly valuable and worth expanding upon. Physics is an incredible subject worthy of transferring into, and MSU's case of interesting major pathways may or may not be a commonality across other similar institutions. What sits aside from this is the ability to communicate with those institutions around you from which students come to learn Physics. Transfer *will happen* into *your* Physics curriculum. It can be as simple as a conversation with those students to build a connection with their experiences. The institutions they come from give context to tons of policy-related experiences, such as whether the institutions have any shared resources, promote state resources, or if there are agreements or programs at all for the benefit of the student. This can be financial, or about specific credit retention, or about the Physics curriculum. It is all worth understanding. Our field of research supports these topics and well more than that. I encourage this work to continue on both in and out of quantitative methodology, in that there is so much more to explore, define, and understand about transfer student experiences.

8.1.2 Toward Institutional Research

Learning about Institutional Research irrevocably changed my perspective of quantitative Education Research. Working with large datasets such as these requires so much more care and consideration and redefining one's knowledge of the education data space than one might think. On introduction to this field, such knowledge seemed intimidating and perplexing at how expansive it was. The information we have access to is full of rich potential for representing our students well and puzzle-piecing together some of their experiences with care. Through our field, we often have to react to the requests asked of us from institutional and national standards, but there is most certainly space for advocation for better practices. Education Research lives in such specific and sometimes niche spaces under the eye of the administration. Institutional Research is so much closer to those who have the power to make change.

Transfer student work is extremely valuable to IR, as it is well within the mission of the institution to understand who its enrollees are and where they are most commonly coming from [145]. Transfer students are a significant part of MSU's population, but regardless of prevalence, they are rich with experiences and policy interaction that can and should be regularly assessed. Speaking with other institutions, especially that are 'top feeder' institutions, provides the opportunity to assess their own data aspirations and understandings of their own students' goals and pathways. It is well worth exploring the option of communicating with fellow IR offices or data analysts for resources that aid the pathway of transfer.

8.1.3 Toward Administration

Research endeavors serve to improve spaces of education. The soap box that creates this dissertation is not one of solely critique for the way that administration is shaped at MSU and beyond. It is encouragement as well, in that historic policy is often upheld but that there is worth to challenging that historic context. As rules and guidelines, policy is not an enemy every time. It can be a guiding hand to the end destination. With that said, transfer students face a multitude of unique policies and framing of success that is harmful to their trajectories through higher education. Data-driven endeavors are highly sought in modern research, but is often overly relied on as the explicit driver of change. That is, data-driven does not always mean quantitative, easy-to-digest measures and numbers. It sometimes means a conversation, opening the doors and keeping a listening ear to what students are actually experiencing in the entire time they are trying to attend your institution. Are you listening? Or is the number the only thing that matters?

8.2 Limitations

From the oldest version of this work to its very end, two of the strongest limitations still stand as the availability and interpretation of the data sources held and the flexibility of what a transfer student can be defined as. Beginning with the first, the original shaping of this work was constructed without explicit connection to the MSUEDW nor NSC data. As we transitioned to official connections of MSU's institutional data, we were then exposed to an entirely different structure to navigate with column names and hundreds of views that we were unfamiliar with. Taking time and finding resources to navigate these yielded some explanations for column names, but not always what the columns are commonly used for. As an example of this navigation struggle, one of our indicators for credit loss is a column using the term 'adjusted' which was not familiar at first, and after utilizing this column for several weeks, we learned from the IR practitioners at MSU that this column is intended to be *summed* over all terms after transfer as the student can accrue more credits and have more adjusted off. We selected the views that we came to understand as accurate and relevant to our work. In this strange form of a limitation, we have many other tables of data that could be combed through for relevance to transfer student experiences or more realms of student success. With more collaboration alongside other practitioners who use this data frequently, we can discover more about the transfer and credit translation process at MSU, more common inquiry or demographic information that might suit transfer student analytics, and more potential policies and metrics to explore.

The latter broad limitation came across through this transition to the MSUEDW as well, as attempting to define who a transfer student is, similarly, encounters a litany of lived experiences that can make for a hundred different constructed definitions. In literature, we explored many realms of transfer student studies that did not differentiate transfer students much beyond the mere action of transferring to a destination institution [46, 66]. Our research fields, however, have made strides with intentionally differentiating between two-year and four-year institution transferring, bringing in terminology such as vertical or horizontal transfer depending on the prior institution type (vertical for having transferred from a two-year institution to a four-year, then horizontal for a four-year to a four-year or two-year to a two-year institution) [30, 74, 94, 101, 128]. An additional unexplored aspect of this rising terminology is that of students who experience 'swirling', usually a phenomenon of multiple institutions in a sort-of back-and-forth manner depending on the types of institutions attended [146, 147]. These studies each broach a limitation of our work in that our focused type of transfer student is slightly variant depending on the data access, acquisition, and curation we could manage, noting that Chapters 5 and 6 share a definition of transfer student explicitly toward those who have *most recently* transferred from a two-year college, whereas Chapter 7 with its low number of Physics students is comprised of *mostly* two-year college transfer students. With the style of Network Analysis and visualization tools chosen, it would be a perfect next step to evaluate graduation differences between these types of Physics transfer students and assess potential enrollment differences. As it stands, MSU defines transfer students with its own rules for doing so, labeling students as either 'transfer' or 'FTIAC', then retaining information of the type of institution transferred from if any. This meant it was increasingly complex to attempt to point out swirling students or nuance of attending very specific types of institutions beyond the information gathered.

Our efforts also were framed for one institution as a sort of 'case study', wherein MSU's goals, practices, and policies vary from other institutions [107, 145]. We are representing the experience of transferring within *our* institution. This narrower scope of a singular institution makes tackling specific policies more feasible, for which we applaud the work of Hodara *et al.* for assessing so deeply the various transfer policy aspects across ten states for commonalities and student and faculty assessment of these policies [7]. While we are able to assess deeper into MSU's happenings, such as within the Physics curriculum, we were subsequently limited from expanding outward by our choice of data sources and policy inquiry.

8.3 Broadest Implications

For all of these lenses considered, transfer student work is incredibly important to higher education. As the modern world faces financial implications around every monetary decision, a students' decision to pursue higher education should not be hindered later on in completion efforts simply because they decided to attend community college first. Stigma and poor experiences with policy are *not uncommon* upon taking the label of transfer student. It is imperative that we change this framing in our own research and tackle the still-existing stigma and harmful policies that act as barriers to completion. Transfer students in critical times of their education, for example holding Junior-level credit status, are still susceptible to making critical changes in their trajectories. We need the resources and research endeavors that help support these students in these critical moments so that they are confident in their successes — while allowing space to not explicitly meet our 'standards' of successes. The traditional means of assessing these students often does not consider who these students are at all, and this also needs to change. We risk losing highly valuable people in our fields, especially STEM, by being uninviting, inconsiderate, and incompetent in our work. As such, it is imperative that we are welcoming, accommodating, and intentional as we continue to work with transfer students in earning their degrees.

8.4 Future Work & Final Word

There are so many paths that this work can and should travel. Transfer students are rich with unique experiences [51, 58, 62, 69, 70]. My recommendations from this work are to continue looking beyond early intervention practices and ask not only what we can add, but what we can change. Future work of this dissertation, with the opportunity to expand on this entire body of work, includes a commonality of 'digging deeper' mentality. There are so many lenses by which we can understand transfer student experiences, and this work managed to hit on a few of these experiences while likely evading several more, such as attending college part-time, assessing specific financial barriers, or perhaps the multitudes of other policies interacted with that are ripe for picking apart through success metrics. Regardless, these experiences are precisely what makes them encounter transfer-based policy and each of the barriers and supports that may come with them.

It is always worth taking a data-driven approach to understanding and reconsidering existing policy structures if and when we notice lack of support in our spaces they work hard to navigate. The financial implications of this work reach every nook and cranny from local classroom and department spaces to the broadest enrollment requirements. This work can easily look at other departments' coursetaking dynamics, graduation statistics, and other interests through the analytic tools shaped, and in a broader sense the reformation of success metrics can be considered through and beyond redefining time-to-degree.

The transfer process is confusing and stifling. Success is arbitrary. Inquiry often exists in unreachable places. It is the intention of data-driven work to find a way for all of these facts to hold hands with each other and figure out where to begin change.

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APPENDIX A

SQL PULLS FROM MSUEDW AND CLEARINGHOUSE

```
SELECT
g.*
FROM siscs.R_STUDENTTERM_RV g
WHERE g.FIRST_TERM_IN_PLAN >= '2105'
    AND g.TERM_CLASSIF_CODE IN ('NEW','CONT','RTRN','RGAP')
    AND g.ENROLLMENT_STATUS IN ('E', 'W')
    AND g.PRIMARY_CAR_FLAG IN ('Y')
    AND g.ACAD_CAREER = 'UGRD'
```

```
SELECT
c.*
FROM ir_clrhouse.NSC_TRAN_PRIOR_ENRL_V c
```

```
SELECT
m.EMPLID,
m.COMPLETION_TERM,
m.DEGR_CONFER_DT,
m.ACAD_PLAN_TYPE,
m.ACAD_CAREER,
m.ACAD_PLAN_DESCRSHORT,
m.EDUCATION_LVL_XLATLONGNAME,
m.EDUCATION_LVL,
m.CIP_CODE,
m.GRAD_TOT_CUMULATIVE,
m.ACAD_PLAN_TRNSCR_DESCR
FROM siscs.R_STUDENTAWARD_RV m
```

```sql
WHERE m.ACAD_DEGR_STATUS = 'A'
    AND m.ACAD_CAREER = 'UGRD'
    AND m.ACAD_PLAN_TYPE = 'MAJ'
    AND m.EDUCATION_LVL = '13'

SELECT
 t.STRM,
 t.TERM_BEGIN_DT,
 t.TERM_END_DT,
 t.ACAD_CAREER
FROM siscs.R_TERM_RV t
WHERE t.ACAD_CAREER = 'UGRD'

SELECT
 n.EMPLID,
 n.SEX,
 n.GENDER_PREF,
 n.IPEDS_RACE_ETHNICITY,
 n.CITIZENSHIP_DESCRSHORT
FROM siscs.R_STDNTBIODEMO_RV n

SELECT
 h.EMPLID,
 h.EXT_ORG_ID,
 h.FROM_DT,
 h.TO_DT
FROM siscs.P_EXT_ACAD_DATA_V h

SELECT
```

```
p.EXT_ORG_ID,
p.EXT_ORG_DESCR50,
p.LS_SCHOOL_TYPE,
p.EXT_ORG_EFF_STATUS,
p.EXT_ORG_COUNTRY
FROM siscs.R_EXTORG_RV p
WHERE p.EXT_ORG_EFF_STATUS = 'A'
    AND p.LS_SCHOOL_TYPE IN ('2YR', '4YR', 'OTR')
    AND p.EXT_ORG_COUNTRY = 'USA'

SELECT
l.EMPLID,
l.ACAD_CAREER,
l.UNT.BILLING,
l.UNT.EARNED
FROM siscs.R_STUDENTCLASS_RV l
WHERE l.ACAD_CAREER = 'UGRD'
    AND l.STRM >= '2102'

SELECT
d.EMPLID,
d.ARTICULATION_TERM,
d.ACAD_CAREER,
d.UNT_TAKEN,
d.UNT_TRNSFR,
d.EARN_CREDIT,
d.SUBJECT,
d.CRSE_CODE
```

```
FROM siscs.R_STUDENTTRANCRSE_RV d
WHERE d.ACAD_CAREER = 'UGRD'
    AND d.ARTICULATION_TERM >= '2102'

SELECT
a.EMPLID,
a.TERM_DESCRSHORT,
a.STRM,
a.COHORT_PRIM_ENTRY,
a.FIRST_TERM_IN_PLAN,
a.ACAD_LEVEL_BOT,
a.ENTRY_STATUS_CODE,
a.ACAD_PLAN,
a.ACAD_CAREER,
a.TERM_CLASSIF_CODE,
c.SUBJECT,
c.CRSE_CODE,
c.CRSE_GRADE_OFF,
c.section_id,
c.crse_id,
n.SEX,
n.GENDER_PREF,
n.IPEDS_RACE_ETHNICITY,
n.RACE_ETHNICITY,
s.COMPLETION_TERM,
s.ACAD_PLAN as ACAD_PLAN_GRAD,
s.ACAD_PLAN_DESCRSHORT,
s.ACAD_PLAN_TYPE,
```

```
s.EDUCATION_LVL
FROM siscs.R_STUDENTTERM_RV a
INNER JOIN
siscs.R_STUDENTCLASS_RV c ON a.EMPLID = c.EMPLID and a.strm=c.strm
INNER JOIN siscs.R_STDNTBIODEMO_RV n ON c.EMPLID = n.EMPLID
LEFT JOIN siscs.R_STUDENTAWARD_RV s ON s.EMPLID = a.EMPLID
WHERE
a.ACAD_CAREER = 'UGRD'
    AND a.ACAD_PLAN IN ('PHYSIC_BS1', 'PHYSIC_BA1', 'PHYSIC_BS2')
    AND a.STRM > '2105'
    AND a.PRIMARY_CAR_FLAG in ('Y')
    AND a.ENROLLMENT_STATUS in ('E')
    AND c.STDNT_ENRL_STATUS='E'
    AND c.class_type='E'

    SELECT
h.EMPLID,
h.EXT_CAREER,
h.EXT_ORG_ID,
h.FROM_DT,
p.EXT_ORG_DESCR50,
p.LS_SCHOOL_TYPE,
p.EXT_ORG_EFF_STATUS,
p.EXT_ORG_COUNTRY
FROM siscs.P_EXT_ACAD_DATA_V h
    LEFT JOIN siscs.R_EXTORG_RV p
    ON p.EXT_ORG_ID = h.EXT_ORG_ID
WHERE h.EXT_CAREER = 'UGRD'
```

```
    AND p.LS_SCHOOL_TYPE IN ('2YR', '4YR', 'OTR')
    AND p.EXT_ORG_COUNTRY = 'USA'
    AND p.EXT_ORG_EFF_STATUS = 'A'

def cohend(d1, d2):
    # calculate the size of samples
n1, n2 = len(d1), len(d2)
    # calculate the variance of the samples
s1, s2 = np.var(d1, ddof=1), np.var(d2, ddof=1)
    # calculate the pooled standard deviation
s = np.sqrt(((n1 - 1) * s1 + (n2 - 1) * s2) / (n1 + n2 - 2))
    # calculate the means of the samples
u1, u2 = np.mean(d1), np.mean(d2)
    # calculate the effect size
return (u1 - u2) / s
```

APPENDIX B

OUTLIER REMOVAL FOR GRADUATION-LEVEL DATA

As we move out of defining the general population, we recognize the typical practice of removing outliers from the dataset. This is a practice in which we say there should be cause for each sample item to not fit into the final population. For FTIAC students, we are not performing much a depth of analysis on them with regards to specific Input Variables or demographics or the like; rather, we are considering 1) the fact that they are a FTIAC rather than a transfer student, and then 2) what their time-to-degrees are at MSU in both of our metric types, eventually in comparison to Transfers. Thus, the only variable to consider balancing is their time-to-degree outcomes (calendar and enrollment), and we can choose to remove outliers. As fitting with the idea of why outliers can be removed in terms of time-to-degree, it's a rather straightforward theme we'll revisit with transfers that is typical: if students have time-to-degree values in either calendar or enrollment that seem too far deviated from the mean of the population, then it is worth considering them as extreme cases and therefore outliers.

After performing the z-score removal on total time-to-degree, 246 transfer students were removed and 832 FTIAC students were removed. Senior-level incoming transfer students were then removed entirely for lack of representation post-outlier removal. As well, transfers who attended more than three prior institutions were removed. After these two removals, we were left with 7,241 students who attended 1-3 prior institutions and are either Freshman, Sophomore, or Junior-level transfer students. We coded transfers as binary attending a single prior or 'more than one' prior institution (i.e., two or three). Removal of the Senior level graduate students, who were at an N of 22 before outlier removal, also was a decision made considering that some exceptions to transfer credit intake can be made for specific programs allowing up to 90 credits transferred in, in conjunction with being too small N to be considered in our statistical analyses.

This population also experienced removal of outlier students whose time-to-degree outcome was a z-score of three standard deviations beyond the mean. This was calculated in Python through *scipy.stats.zscore*, which calculates based on the columns inputted what rows contain values beyond three standard deviations away from the mean in each of the respective columns, omitting outliers. This helps to begin normalizing the data for representation in the study. We considered removing outliers within transfer students in the columns of **adjusted credit** and **incoming transferable credit**, as these are important bases of measurement in later analyses, but opted not to, which we will describe below.

For Chapter 6, we utilize the same dataset and pulls from Chapter 5, with a few additional and a few disconsidered pulls. As in Chapter 5 we had a couple of auxiliary (i.e. optional) pulls that might supplement approximate prior institution data in the case of no access to the NSC, this chapter circumvents these SQL pulls and we continue using the same joins as prior. We also continue using NSC data in order to represent the enrollment-based time-to-degree, as we are using this as the main metric of measuring time-to-degree outcomes as related to credit loss. New SQL pulls are comprised of pulls oriented toward displaying prior coursework and continuing to display the number of transferred credits on enrollment. With these we are able to discern the type and amount of credits accrued per student from prior institutions, as well as the type and amount that were accepted as transferable to MSU. This is an important language distinction: the translation of credits that occurs must meet a few requirements in order to be accepted for transfer, then thereby being considered 'transferable'. The total amount of credits held by these students being called 'transferable' is defined as such because the decision of which credits are adjusted is part of the Black Box arrangement; it is typically a nebulous selection of those credits based on least applicability at any certain time in a student's pathway.

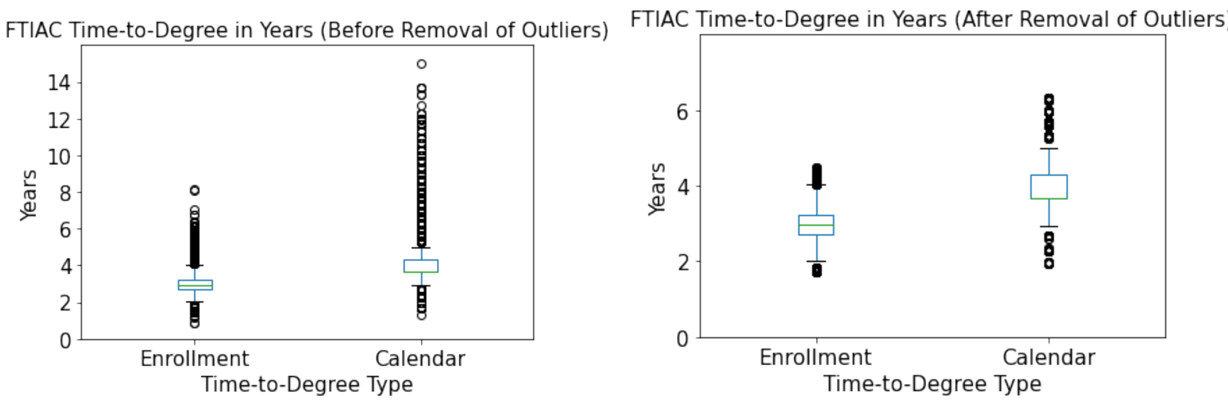
To round out the data cleaning portion for Chapter 6, we performed the same data cleaning methodology with respect to the recurring SQL joins from Chapter 5, as well as the same removal of outlier students through 'z-score' methods on both types of time-to-degree, but this time we lose an additional 12 students through the joining of the new SQL(s) as there may be some missing data on prior coursework, which requires further investigation. For clarity, the 12 missing students were assessed and their incoming credit information was incomplete. As well, they all transferred in at Freshman level status, which could indicate some form of translation error or an indicator of being a part of a certificate program at MSU prior to coming in. The additional information around courses transferred into MSU does not impact this outlier removal, nor does the level of adjusted credits, considering the dialogue we centered around importance in levels of adjusted credit among Juniors, who are heavily impacted when subjected to outlier removal in credit-based variables.

There is a lot of discussion around how to correctly perform outlier removal. Between different statistical tests, there are criteria for normalizing or getting data relatively 'in-shape' for what is satisfactory to the assumptions of those tests. So what does it mean to remove outliers for the remaining student set of transfers? We removed for FTIACs in both time-to-degree metrics, and will continue this into the transfer student population, but we also consider that there is another transfer-specific metric that may produce significant outliers in the form of credits. The story of transferring credit includes cases of students who carry an inordinate amount of credit with them and, therefore, could experience a high amount of adjusted credit loss. This is similar to the reasoning behind removing students who have previously earned a Bachelor's degree, as the merit of earning the Bachelor's at MSU is dependent on the reasonableness of the pathway as similar to their peers. We may see Junior level incoming transfer students bringing in the highest reasonable amount of credits, but in Seniors we start to anecdotally observe students in specific programs that have more credit allocation ability. In a harder decision, we also know our adjusted credit is not normally distributed, as the grand majority of transfer students do not have any adjusted credit.

Removing outliers in adjusted credit in particular is complex. The z-score method does not technically have a requirement for data to be distributed normally, but in practice the outlier removal process requires an understanding of what stories one omits by removal of those outliers. The fact for our data is that any transfer student can have their credit adjusted, but most of them do not. Removing outliers is biased toward those who have any amount of adjusted credit, and we see that the typical removal of outliers within the whole population of adjusted credit removes only Junior-level transfer students and at a rate of 8% of their population. The standards of how many outliers removed being acceptable varies, but with only removing outliers in time-to-degree outcomes, we keep this threshold below 7% instead of continuing to remove more students. We also consider the clear implication that Juniors also have more transferable credit by proxy, and therefore on interaction with the 60 credit transfer limit policy, we would be conflating a known categorical distinction of transfer students with removing a 'continuous' variable that is not normally distributed. Therefore, we make a decision to continue with what we did for FTIACs and removing outliers with respect to our outcome variables of calendar and enrollment time-to-degree, which we will track what occurs with the other credit variables and amount of students left per academic level of entry. Transfers are decided by the total time-to-degree in higher education variables, whereas FTIACs are decided by the total time-to-degree values at MSU.

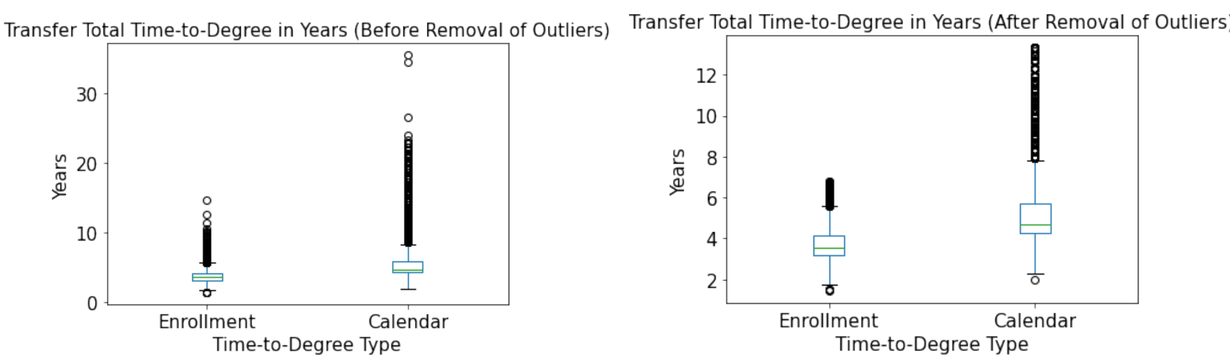
Before and after removal of outliers, we generate boxplots to view what occurs in both populations of FTIACs and transfers in their time-to-degrees and other notable categories. FTIAC outlier in time-to-degree removal can be viewed in Figure B.1a, B.1b as a boxplot representing the range of years for both metrics, which we will view the averages of in the Results section. Transfer outlier removal can be seen in Figure B.2a, B.2b as boxplots, showcasing a similar range decrease of within time-to-degree. Viewing both transferable and adjusted credit within transfer students, which are *not* criteria for outlier removal, Figure B.3a, B.3b shows that there are still many students with a large amount of credits available for transfer and adjustment. The mean of adjusted credit does not change, as the majority of transfer students do not experience *any* adjusted credit.

On a last note about the removal of outliers particularly for transfer students, of students removed after time-to-degree z-score paring, the average amount of adjusted credit among the 260 initially removed students was 14.2 credits, which is more than a full term of credits. The average transferable credits among the 260 outlier students was 70.9 credits. 48.1% of these removed students attended two or more prior institutions.



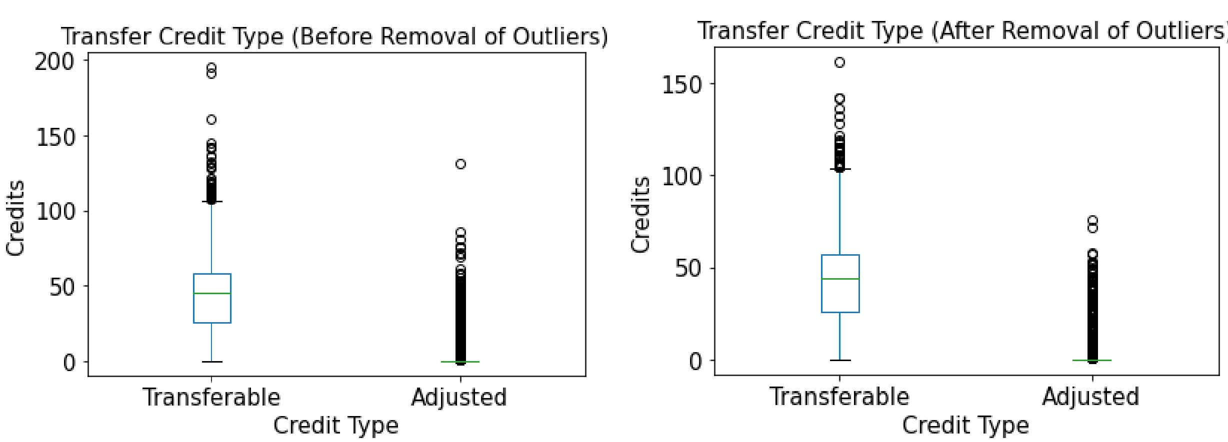
(a) FTIAC Time-to-Degree prior to outlier removal (b) FTIAC Time-to-Degree after outlier removal

Figure B.1 After removal of outliers, maximum TTD does not exceed 7 calendar years or 5 enrolled years.



(a) Transfer Time-to-Degree prior to outlier removal (b) Transfer Time-to-Degree after outlier removal

Figure B.2 After removal of outliers, maximum TTD decreases by over 20 calendar years or 7 enrolled years.



(a) Transfer Credit Type prior to outlier removal (b) Transfer Credit Type after outlier removal

Figure B.3 After removal of outliers, maximum transferable credit does not exceed 150 credits and maximum adjusted credit hits 75 or below adjusted credits.

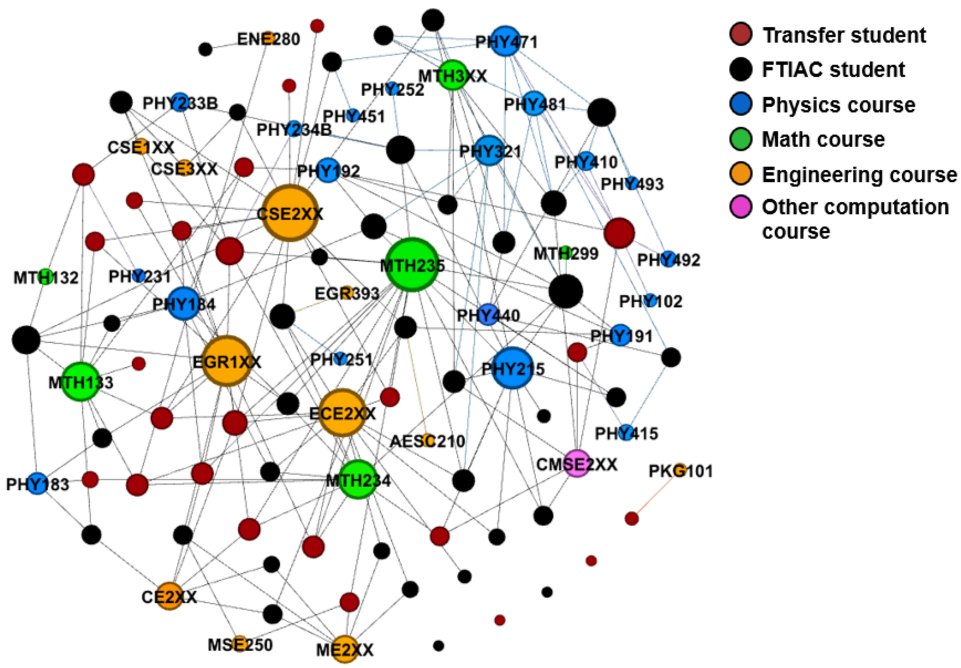


Figure C.1 Generated Network plot depicting the courses enrolled by Physics Juniors in the Academic Year of 2017. Courses are color-coded by subject relevance, including Engineering, Physics, Mathematics, and a special computation course. Transfer and FTIAC students are distinguished as dark red and black respectively.

APPENDIX C

SUPPLEMENTARY MATERIAL - CHAPTER 7 NETWORK PLOTS

Here, we provide several plots created to showcase the interesting interactions with the Gephi-created Network plots. Figures C.1 and C.2 are both displayed in Chapter 7, as well as Figure C.4 as an in-study example of the interactivity of Gephi, but these three are all kept here as reference for the remaining interactive plots and to keep relevant plots together.

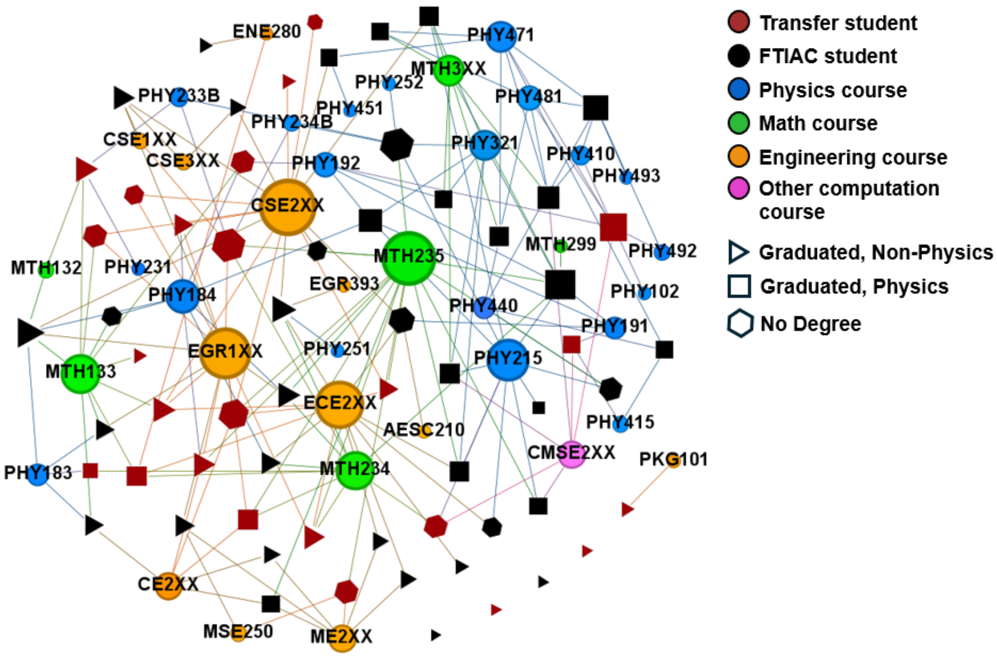


Figure C.2 Generated Network plot which shows the specific graduation status of each student enrolled along with the courses they are enrolled in per Academic Year 2017 as Physics Juniors. Students who graduated with Physics are depicted as squares and those who graduated in a non-Physics major are depicted as triangles. Those who did not graduate are depicted as hexagons. The color distinctions between courses and students remain the same as prior.

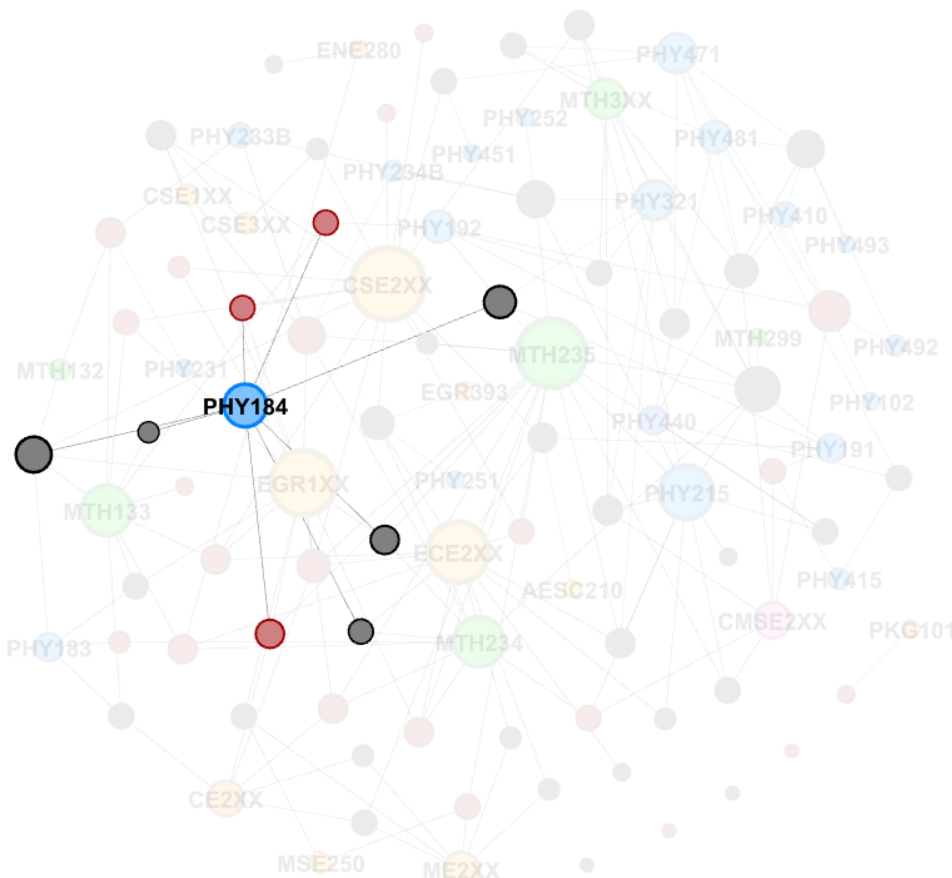


Figure C.3 Network plot depicting Physics 184 (Introductory Calculus-based Electricity & Magnetism, 'Freshman-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 3 transfer students and 5 FTIAC students are enrolled in 2017 for a total of 8 students.

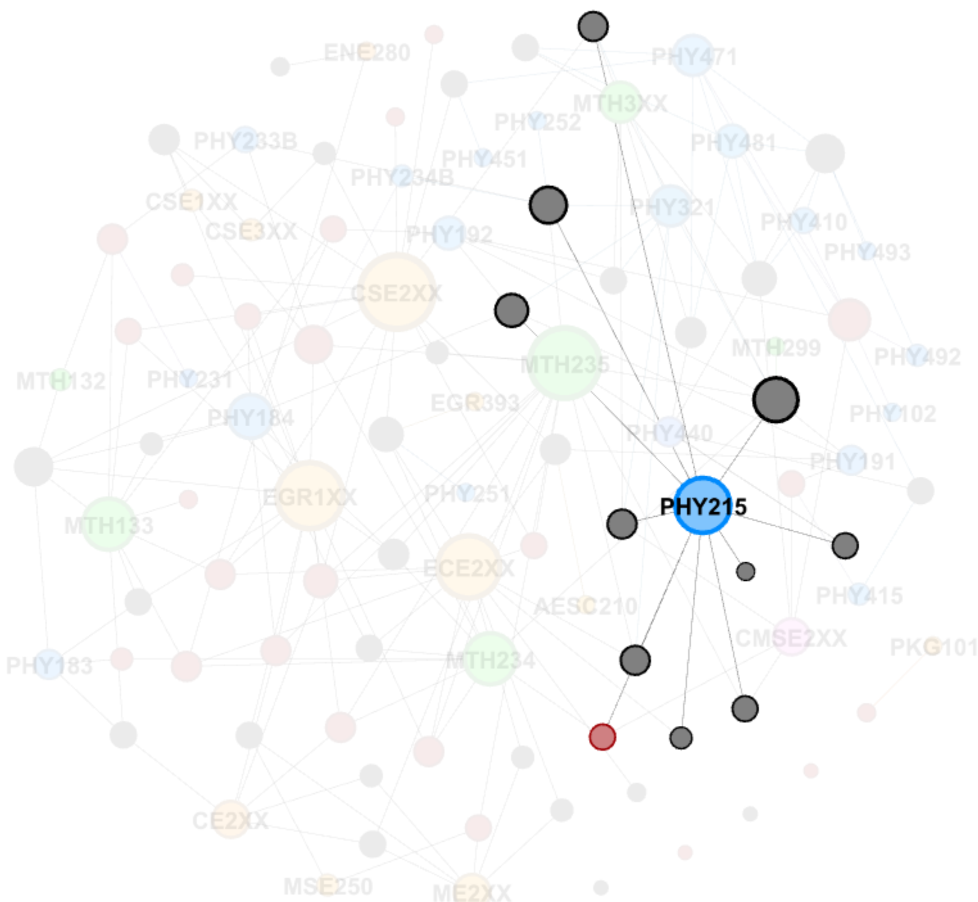


Figure C.4 Network plot depicting Physics 215 (Modern Physics, 'Sophomore-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 1 transfer student and 10 FTIAC students are enrolled in 2017 for a total of 11 students.

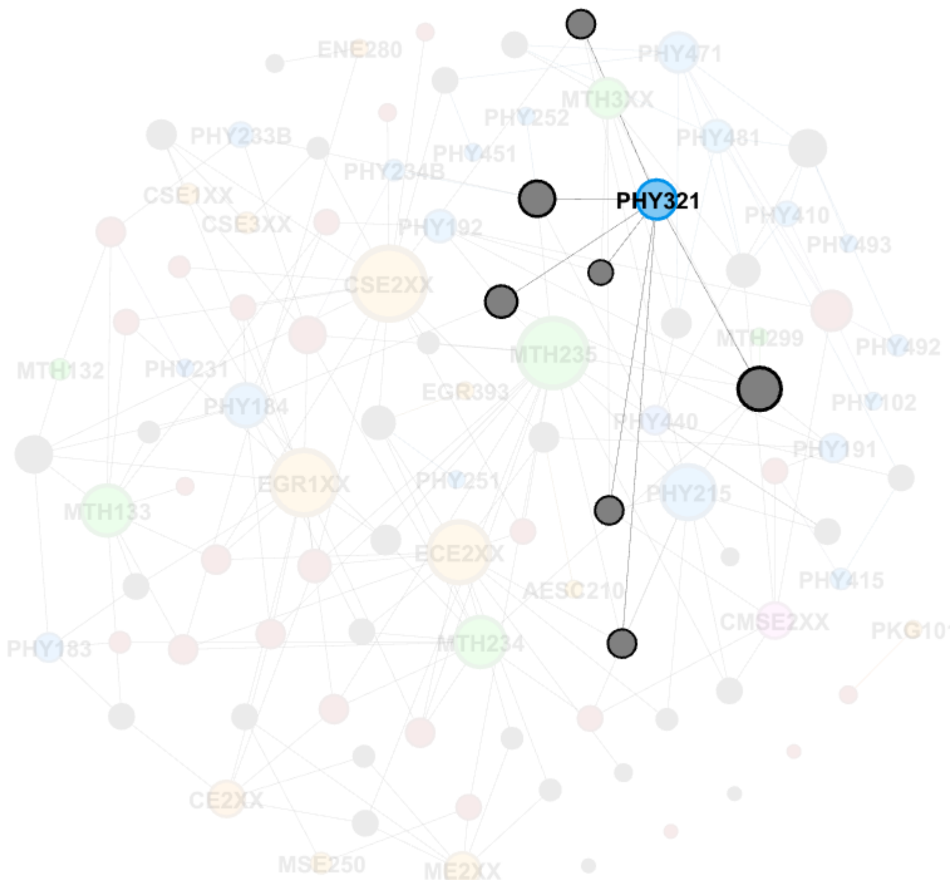


Figure C.5 Network plot depicting Physics 321 (Classical Mechanics, 'Sophomore-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 7 FTIAC students are enrolled in 2017 and no transfer students are enrolled.

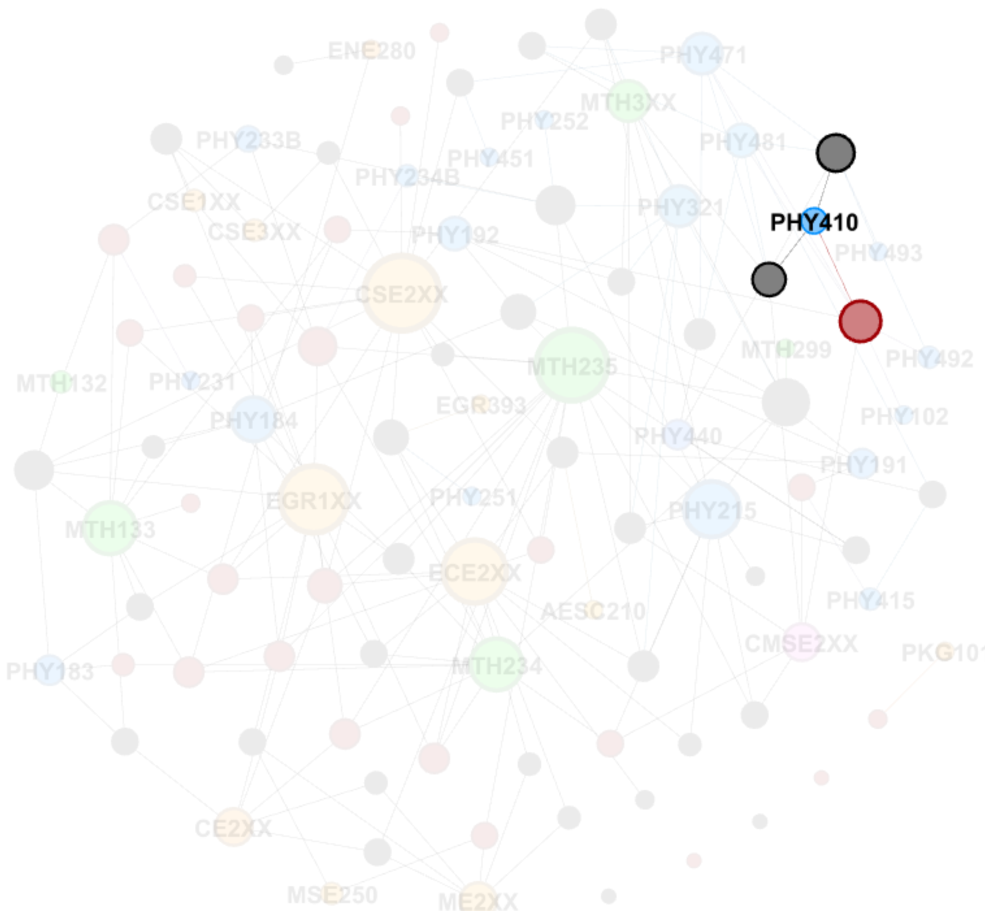


Figure C.6 Network plot depicting Physics 410 (Statistical Mechanics, 'Junior-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 1 transfer student and 2 FTIAC students are enrolled in 2017 for a total of 3 students.

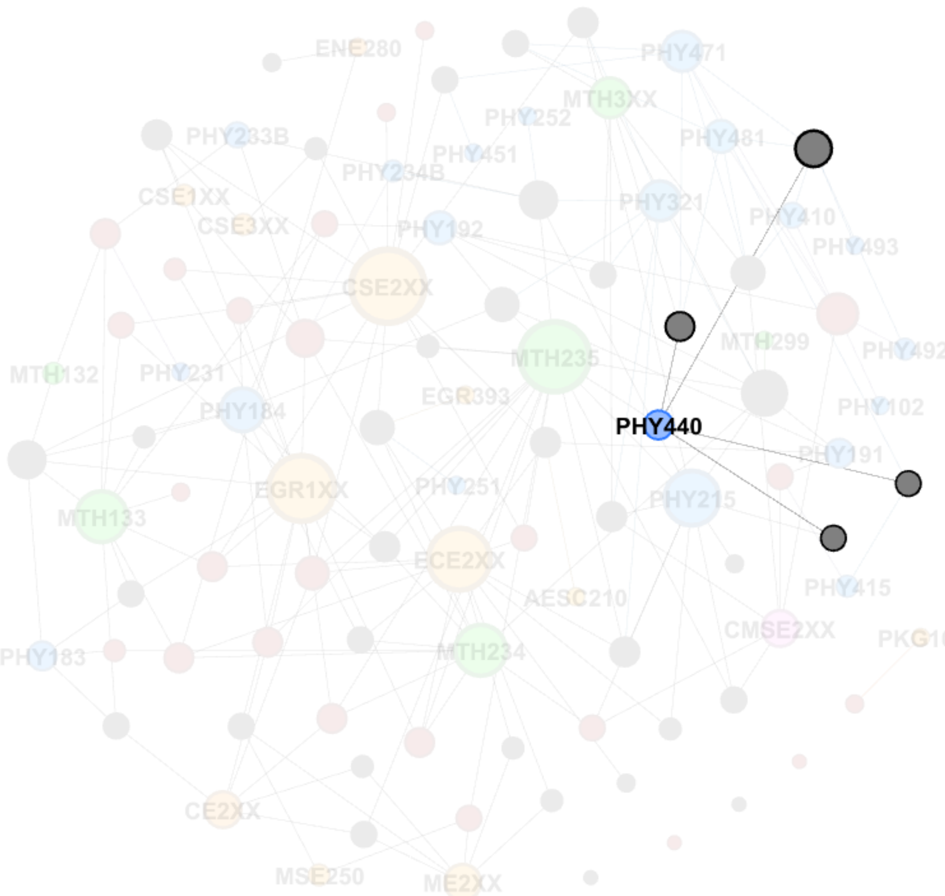


Figure C.7 Network plot depicting Physics 440 (one of two required labs between Electronics and Optics, ‘Junior-level’) enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 4 FTIAC students are enrolled in 2017 and no transfer students are enrolled.

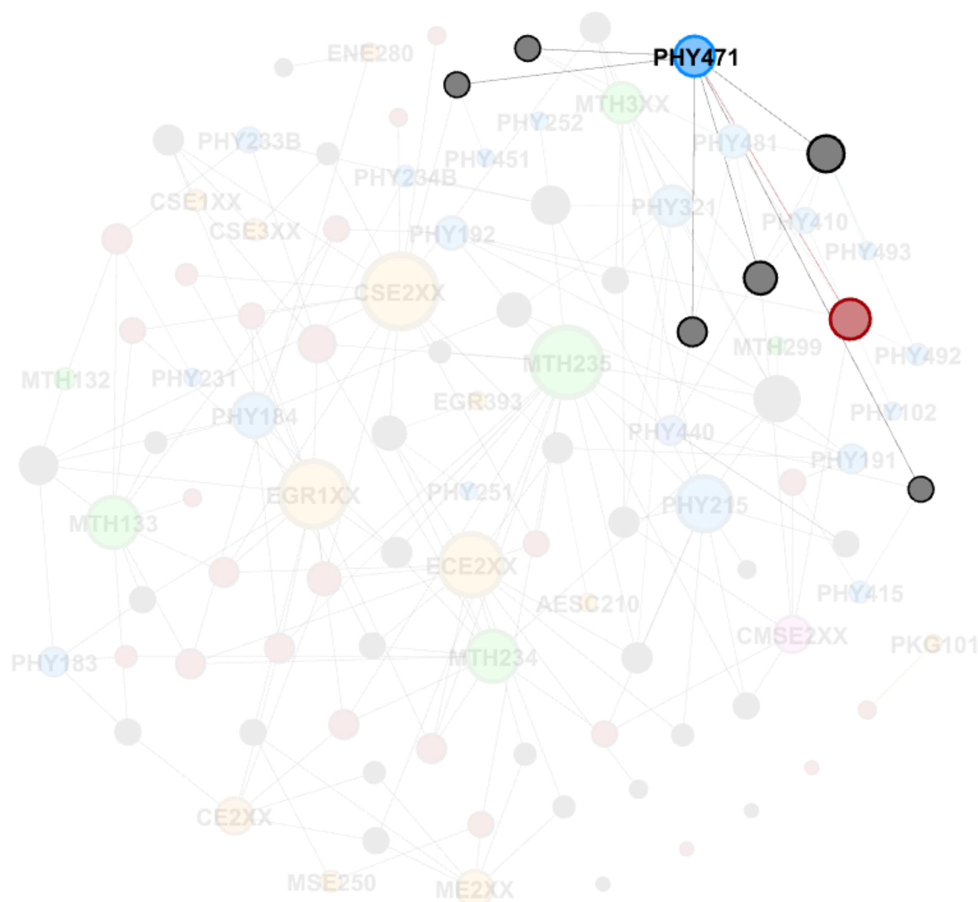


Figure C.8 Network plot depicting Physics 471 (Quantum Mechanics I, ‘Junior-level’) enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 1 transfer student and 6 FTIAC students are enrolled in 2017 for a total of 7 students.

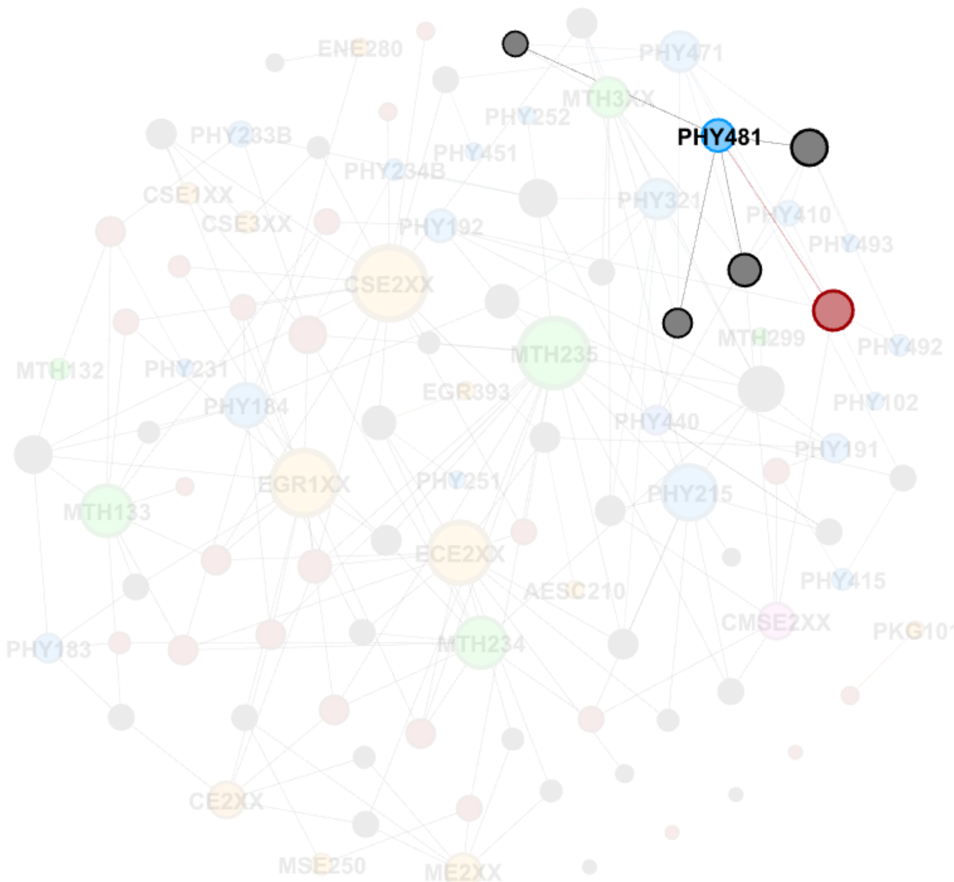


Figure C.9 Network plot depicting Physics 481 (Electricity & Magnetism I, 'Senior-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 1 transfer student and 4 FTIAC students are enrolled in 2017 for a total of 5 students.

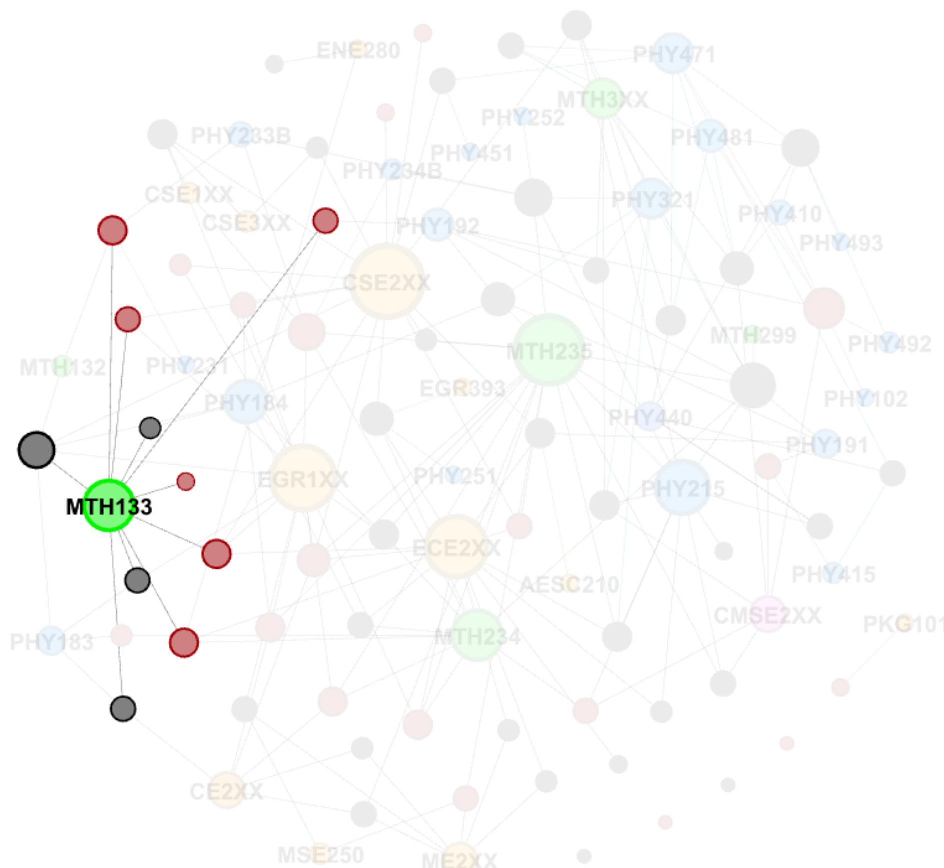


Figure C.10 Network plot depicting Math 133 (Calculus II, 'Freshman-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 6 transfer students and 4 FTIAC students are enrolled in 2017 for a total of 10 students.

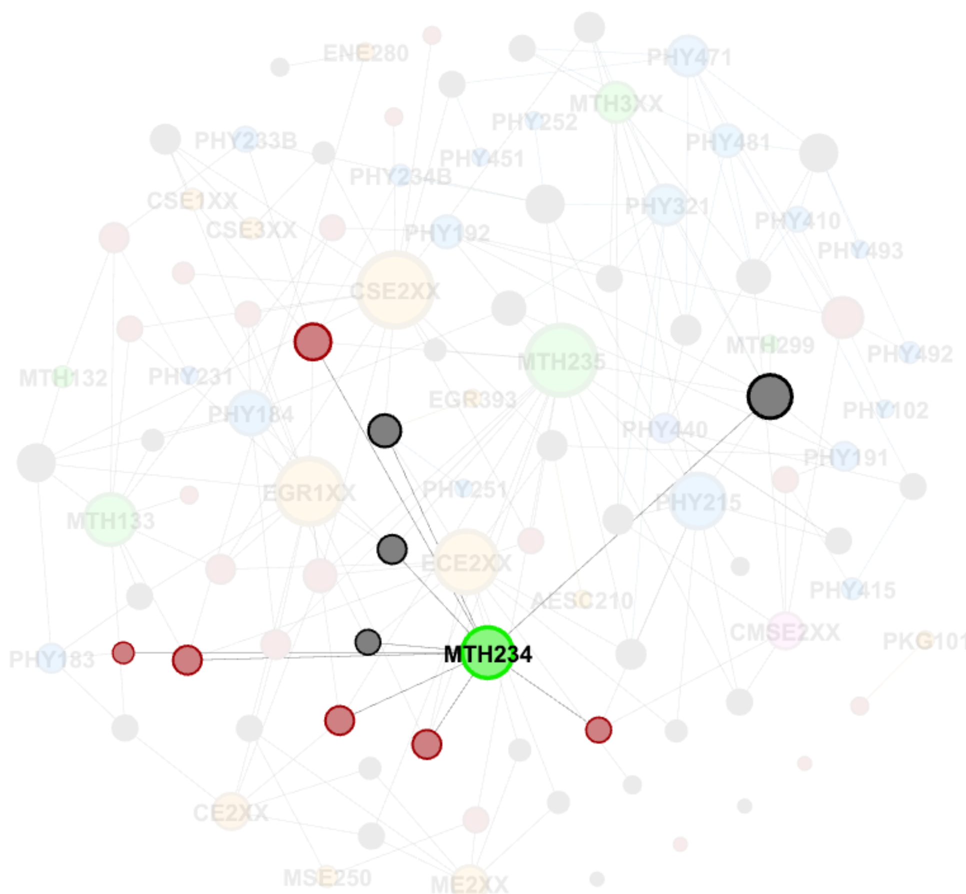


Figure C.11 Network plot depicting Math 234 (Calculus III, 'Sophomore-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 6 transfer students and 4 FTIAC students are enrolled in 2017 for a total of 10 students.

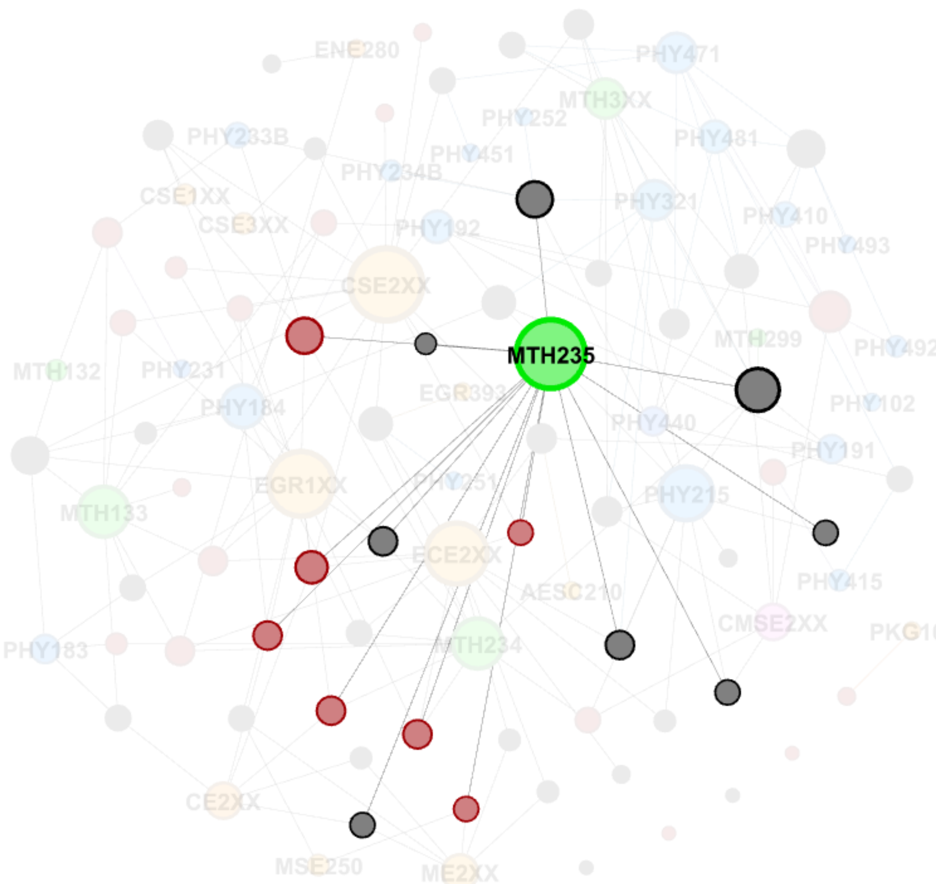


Figure C.12 Network plot depicting Math 235 (Calculus IV or Differential Equations, 'Sophomore-level') enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 7 transfer students and 8 FTIAC students are enrolled in 2017 for a total of 15 students.

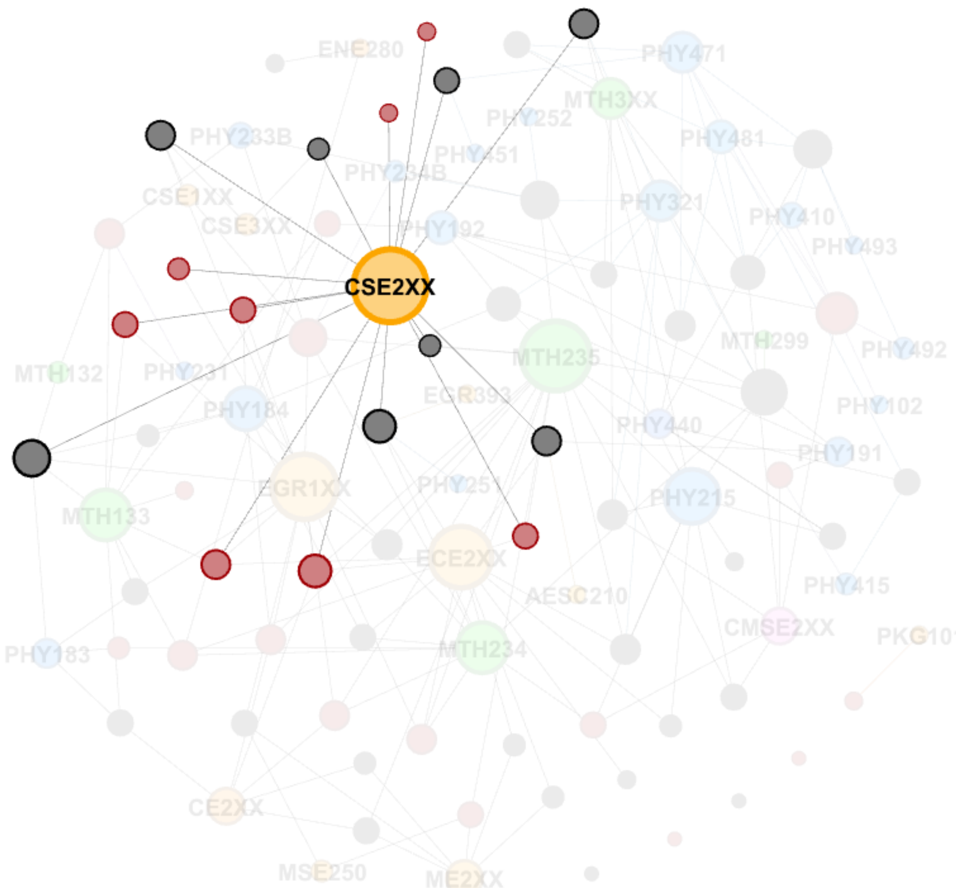


Figure C.13 Network plot depicting Computer Science and Engineering 2XX (various 200-level CSE courses) enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 8 transfer students and 8 FTIAC students are enrolled in 2017 for a total of 16 students.

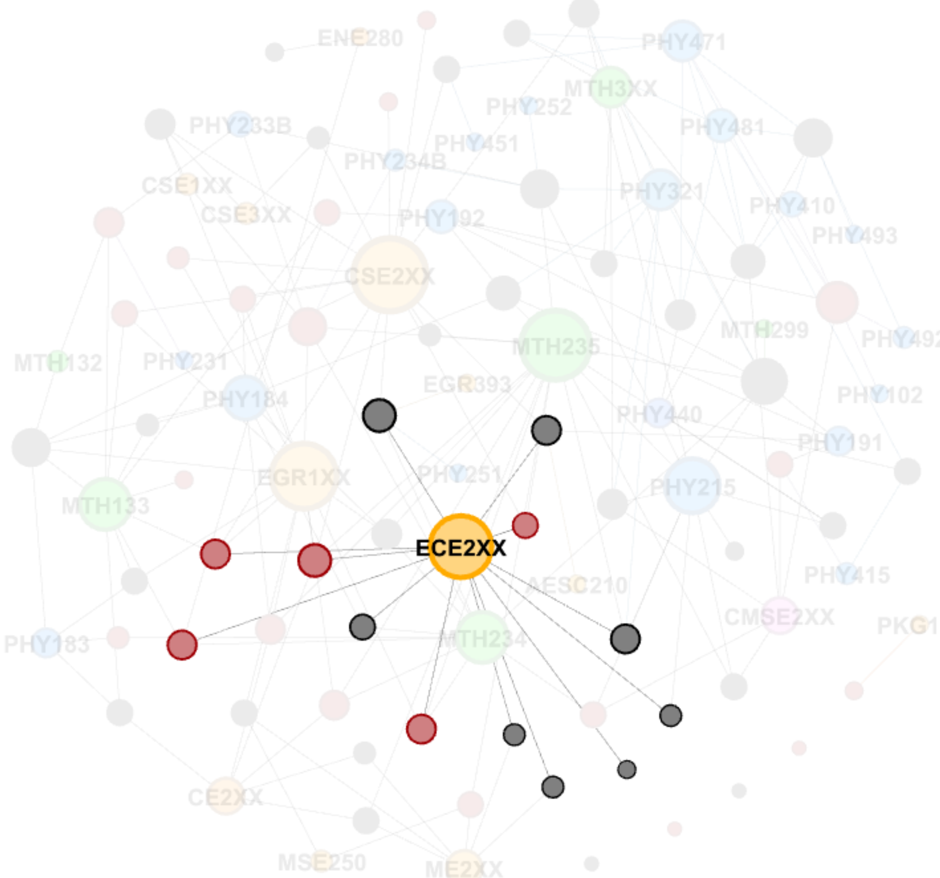


Figure C.14 Generated Network plot depicting Electrical Engineering 2XX (various 200-level ECE courses) enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 5 transfer students and 8 FTIAC students are enrolled in 2017 for a total of 13 students.

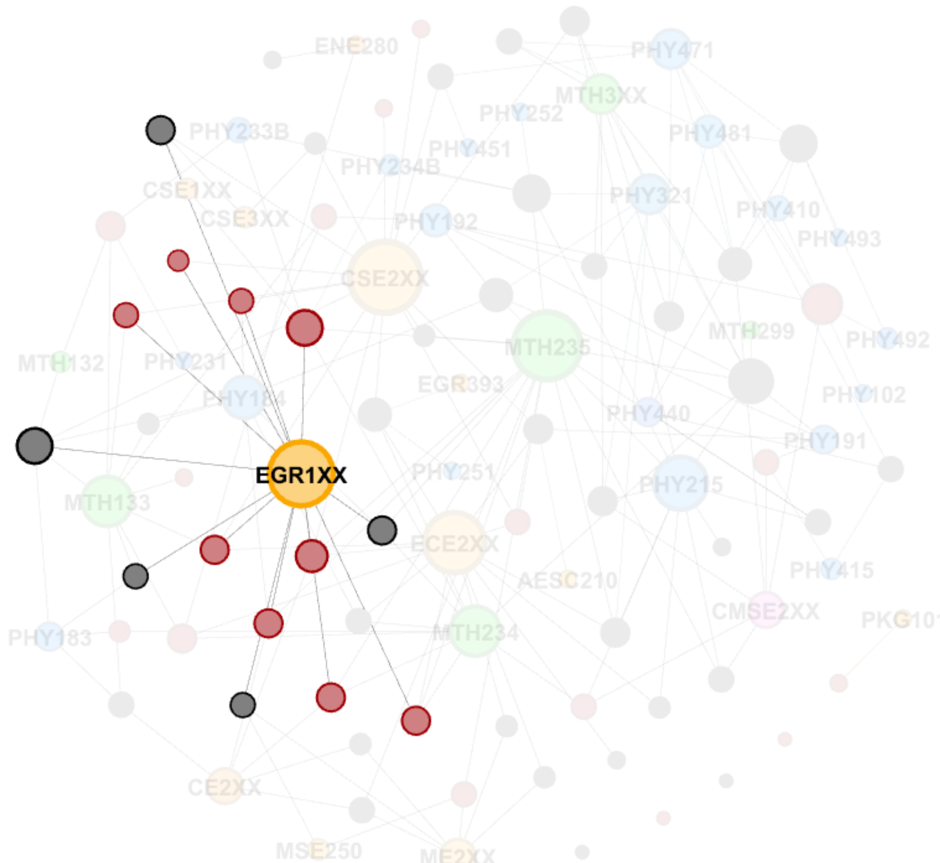


Figure C.15 Generated Network plot depicting Engineering 1XX (various 100-level EGR courses) enrolled in by Physics Juniors in the Academic Year of 2017. Transfer and FTIAC students are distinguished as dark red and black respectively. Here, 9 transfer students and 5 FTIAC students are enrolled in 2017 for a total of 14 students.